Applied Energy 239 (2019) 1402–1423

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Generating linked technology-socioeconomic scenarios for emerging energy transitions

Mitchell J. Small[a,b,*], Gabrielle Wong-Parodi[b], Benjamin M. Kefford[c], Martin Stringer[c], Diego R. Schmeda-Lopez[c], Chris Greig[c], Benjamin Ballinger[c], Stephen Wilson[c], Simon Smart[c]

[a] Department of Civil and Environmental Engineering, Carnegie Mellon University, United States
[b] Department of Engineering and Public Policy, Carnegie Mellon University, United States
[c] Dow Centre for Sustainable Engineering Innovation, School of Chemical Engineering, The University of Queensland, Australia

HIGHLIGHTS

- A Bayesian network model is used to generate scenarios for a new energy technology.
- Scenarios consider technical and sociopolitical factors and their interactions.
- Application to CCS predicts that improvements in both sets of factors are necessary.

ARTICLE INFO

Keywords:
Energy system transitions
Decarbonisation
Carbon capture and storage (CCS)
Bayesian Belief Network (BBN)
Expert judgment
Scenario generation

ABSTRACT

The formulation and use of scenarios is now a fundamental part of national and global efforts to assess and plan for climate change. While scenario development initially focused on the technical dimensions of energy, emissions and climate response, in recent years parallel sets of shared socio-economic pathways have been developed to portray the values, motivations, and sociopolitical and institutional dimensions of these systems. However, integrating the technical and social aspects of evolving energy systems is difficult, with transitions dependent on highly uncertain technological advances, social preferences, political governance, climate urgency, and the interaction of these elements to maintain or overcome systemic inertia. A broad range of interdisciplinary knowledge is needed to structure and evaluate these processes, many of which involve a mix of qualitative and quantitative factors. To structure and facilitate the necessary linkages this paper presents an approach for generating a plausible range of scenarios for an emerging energy technology. The method considers influences among technical and social factors that can encourage or impede necessary improvements in the performance and cost of the technology, as well the processes affecting public acceptance and the establishment of governance structures necessary to support effective planning and implementation. A Bayesian network is used to capture relationships among the technological and socioeconomic factors likely to affect the probability that the technology will achieve significant penetration and adoption. The method is demonstrated for carbon capture and storage (CCS): a potential technology on the pathway to deep decarbonization. A preliminary set of expert elicitations is conducted to illustrate how relationships between these factors can be estimated. This establishes a prior or baseline network that can be subsequently analyzed by choosing either optimistic or pessimistic assumptions for respective groups of technical and social variables, identifying sets of key factors that limit or encourage successful deployment.

1. Introduction

A number of different modeling approaches have been used to explore the character and implications of alternative energy futures [1–7]. In recent years models that utilize a scenario-based approach have been shown to provide a particularly effective means for envisioning the broad features of alternative economic, energy, and environmental trajectories [5–15]. While a classical scenario analysis avoids the assignment of explicit probabilities to different outcomes [13], the requirement that each scenario be self-consistent (e.g., [1,14,16]) provides impetus for more formal methods of uncertainty analysis, which are now being applied to scenario-based assessments [15]. Because

* Corresponding author.

https://doi.org/10.1016/j.apenergy.2019.01.215
Received 23 May 2018; Received in revised form 31 October 2018; Accepted 17 January 2019
Available online 19 February 2019

Table 1
Five scenarios and their computed mean values for selected model outputs.

Scenario	Technical inputs[a]	Social inputs[b]	- - - - - - - - Output variable and mean value predicted for given scenario (0–1 scale) - - - - - - - - 8. Capital cost[c]	10. Operating cost[c]	11. Strength of subsidies	29. Local political support	32.Perceived risk[c]	33. Perceived benefits	36. Prob[H or VH deployment] (%)
1. Baseline (Fig. 1)	Expert informed	Expert informed	0.51	0.38	0.3	0.46	0.6	0.35	21
2. Fully pessimistic	Pessimistic	Pessimistic	0.69	0.69	0.31	0.31	0.60	0.36	5
3. Technology constrained	Pessimistic	Optimistic	0.69	0.69	0.69	0.66	0.45	0.65	25
4. Socially constrained	Optimistic	Pessimistic	0.31	0.32	0.31	0.34	0.58	0.36	32
5. Fully optimistic	Optimistic	Optimistic	0.31	0.32	0.69	0.66	0.43	0.65	70

[a] 1. Existing Pipeline Network, 2. Transport Distance[c], 3. Technology Maturity, 4. Avg. Injectivity, 5. Fuel Costs (and efficiency)[c].
[b] 13. National Public Support for Alternatives[c], 14. National Public Support (for CCS), 15. Outcome Efficacy, 16. Local Activism[c], 17. Land Use Competition[c], 21. Landowner Compensation 22. Public Knowledge, 23. Public Consultation, 24. Regulatory Framework Clarity.
[c] The variable is more supportive of CCS deployment when it is lower (that is, closer to 0 than to 1).

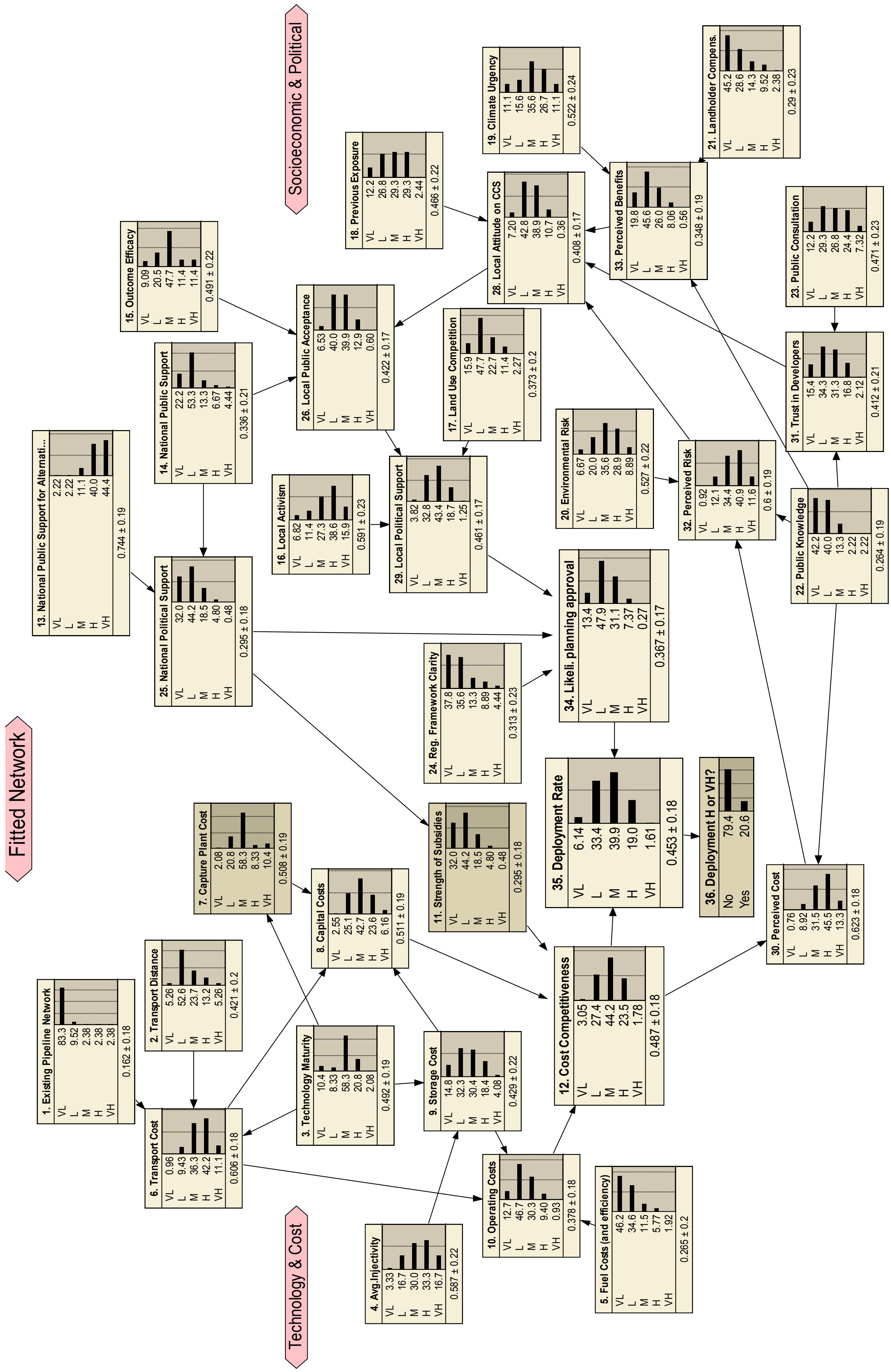
many of the elements of scenario models for future technologies are subjective, cannot be assessed through repeated experiments, and are amenable only to calibration (not validation), results from the scenario modeling approach are understood to provide only soft inferences over a broad range of plausible outcomes.

This paper proposes a method for generating scenarios for the adoption and penetration of low-carbon energy technologies. The method builds upon the Shared Socioeconomic Pathways (SSP) scenario framework for climate change research described, for example, by [9,12,17–21]. In the SSP approach alternative CO_2 concentration and forcing level outcomes are paired with proposed socioeconomic reference pathways to identify the mitigation and adaptation challenges associated with each. Five principal SSPs have been constructed representing a range of future socioeconomic, governance and technology conditions. These include: SSP1, sustainable low-impact growth; SSP2, middle of the road growth consistent with historical trends; SSP3, development with a lack of cooperation between regions; SSP4, high levels of social inequality both within and between regions; and SSP5, high energy use and carbon intensity. A set of demographic, social, economic, technological, and governance elements are used to characterize each SSP (see Table 1 in [9]), and many of these are similar to the variables included in our model.

In this study we build a multicomponent model to generate scenarios for a specific technology: carbon capture and storage (CCS). CCS is a low-carbon technology that involves capturing carbon dioxide from point sources such as coal-fired power plants and injecting it deep underground for assumed permanent storage in geological formations, rather than allowing it to be released to the atmosphere. CCS may be utilized as a means of extending the use of fossil fuels for energy generation while still achieving partial goals for decarbonization of the energy system (e.g., [22]). The potential for CCS to participate in a low-carbon energy mix is significant, and the IPCC in their fifth assessment report (AR5) includes some form of carbon capture technology for the majority of their scenarios for keeping warming below a 2 °C increase from pre-industrial levels [23], and (not surprisingly) similar results are obtained with a more ambitious goal of limiting the temperature increase to below 1.5 °C [20]. However, a number of barriers have, or may in the future, impede acceptance and implementation of CCS [24–27]. The proposed methodology seeks to relate and synthesize these factors and their influence on the success of CCS adoption.

The scenario approach in this paper is structured around the use of a Bayesian network model to capture and explore influences among the factors affecting technology advancement, acceptance, and adoption. Bayesian network models have been applied to a wide range of technology, risk, safety, health, and climate problems – to characterize system uncertainty, assess information needs to reduce uncertainty, and compare risk management options (e.g., [28–35]). In addition, Bayesian networks have recently been applied to generate scenarios for energy and climate assessments [36–42].

In a technology-specific application with similar objectives to ours, Gambelli et al. [38] use a Bayesian network to construct scenarios for the adoption of biofuels from microalgae in Italy. The network includes an interacting set of economic and policy variables, including GDP growth, oil price, technological progress for biofuels, attitudes towards sustainable lifestyles, climate change urgency, the market for novel food and feed from microalgae, water and land requirements for alternative biofuel production processes, and the environmental and climate policies that are adopted. Parameterization of the network model is implemented using a structured process of expert elicitation. Multiple scenarios are generated by the network model, with the most optimistic predicting a 75% probability that biofuels from microalgae will exceed 20% of the biofuel market by 2030, conditioned on specific technological, market, and policy outcomes in this scenario. Our approach and methods build upon those of Gambelli et al., though employing a higher degree of disaggregation of the technical, cost, social and regulatory components that affect CCS adoption. We employ novel methods for



(caption on next page)

Fig. 1. CCS BBN structure (with probabilities calculated following incorporation of expert judgment and survey results).

incorporating expert judgments regarding influences among factors, though only with an initial set of experts and elicitations. As such this application should be viewed as primarily a demonstration of methodology, providing further proof of concept for the use of Bayesian networks for producing self-consistent technical and socioeconomic scenarios for energy and climate assessments.

2. Methods

2.1. Scenario development with Bayesian Belief Networks

A Bayesian Belief Network (BBN) is used to model probabilistic relationships among multiple variables. The nodes of the network correspond to individual variables, with arrows between nodes signifying a causal influence from the upstream (parent) node(s) to the downstream node(s). Node values are typically defined by discrete states (this is especially useful for qualitative factors), though the states may also correspond to the discretized values of continuous or integer variables that are represented by the node. Influence is quantified through the conditional probability table (CPT) of the child node, which shows the probability of each downstream state for each possible combination of upstream parent states. BBNs are able to propagate influence forward through the network using sequential conditional probability calculations. They may also propagate probability updates backward (and throughout) the network using simultaneous application of Bayes Rule, so that a posterior probability distribution for the states in each node is calculated, conditioned on the particular values selected for one or more nodes where observations are made or policy options selected. The posterior network model corresponds to a general scenario (or storyline) which can then be sampled to simulate specific scenario outcomes, each with one state assigned to each node. Model variables that exhibit correlation in the network yield correlated states in the simulated scenarios, so that statistical consistency is maintained across the set of scenario outcomes.

BBNs do have limitations. The network structure must be acyclic (the downstream influence of a node cannot circle back upon itself) and it is often difficult to depict changes in the network over time, unless the entire network is replicated for each time step. However, dynamic BBNs are beginning to see applications [43,44] and this should enable an even broader set of analyses in the future. Various software packages are available for building and implementing BBNs [45] and we utilize one such program, Netica [46], in this study.

The parameters of the BBN include the prior and conditional probabilities that relate upstream (parent) and downstream (child) nodes. These may be estimated using observed data for combinations of nodes, statistical models for these data, or mechanistic process models evaluated with Monte Carlo uncertainty analysis. In this study the data and models for these approaches are generally unavailable, especially for relationships among qualitative variables and those that involve predictions for future outcomes, so that expert judgment is the only feasible method for probability assessment. We thus rely primarily upon expert judgment, illustrating a combination of elicitation and survey methods, to derive and learn the parameters of our BBN. Once the network probabilities are estimated, the model is evaluated to determine the likelihood of different overall system outcomes under different scenario assumptions.

2.2. Model structure and inputs

A preliminary set of model formulation and parameter estimation steps was undertaken in this study. Once the initial structure of the network was developed, a set of international experts, chosen based on their broad expertise in the technical and social dimensions of CCS (n = 4) was then elicited to assess the direction and relative importance of upstream (parent) nodes on downstream (child) nodes by assigning weights to each parent and by indicating the level of confidence in their weight assignments. Given these inputs, the conditional probability table (CPT) for each child was calculated using an approximate method to assign probability across each row of a CPT. In an additional phase of obtaining expert input for the BBN, a survey (n = 49) was developed and distributed by email to known experts and affiliates, asking them to identify what they believe are the most likely states for variables corresponding to the nodes in the network. Further details on these model formulation and estimation steps are now provided, acknowledging the illustrative nature of the fitted model and its intended use as a proof of concept of the overall method.

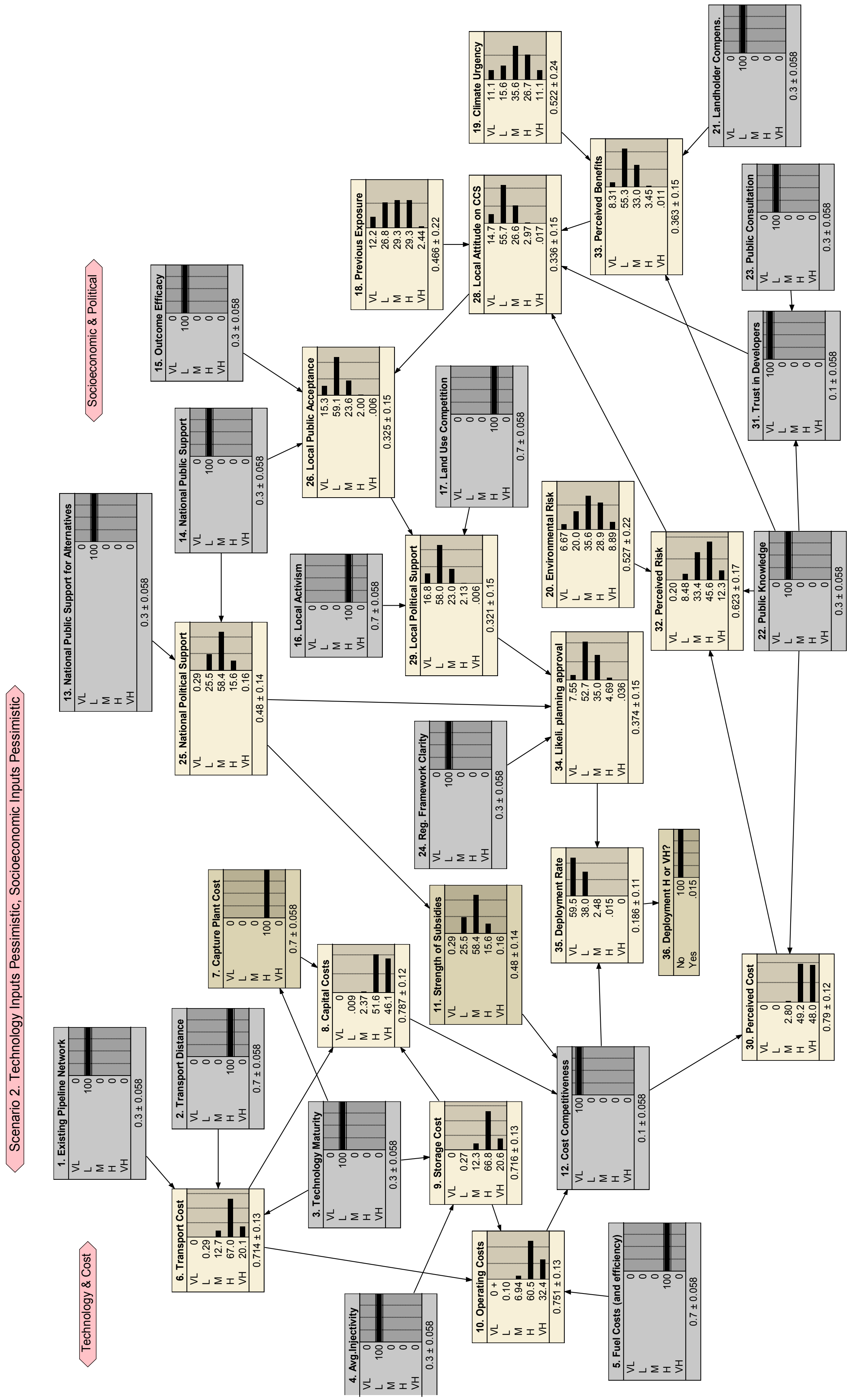
2.2.1. CCS BBN model

The structure of the CCS BBN model is shown in Fig. 1. The states for each node follow a semi-quantitative Likert scale ranging from very low (VL) to very high (VH), with corresponding numerical values assigned over the range (0,1) as: VL = 0.1; L = 0.3; M = 0.5; H = 0.7; and VH = 0.9. The horizontal bars within each node indicate the calculated probabilities (as a percent) for each state. The numbers in the lower box of each node indicate the calculated mean and standard deviation resulting from the assigned numerical value and the calculated probability for each state. The probabilities shown for the states in each node result from the incorporation of expert input into an "informationless" network with all conditional and node probabilities uniformly distributed across possible states. We first discuss the structure of the network in Fig. 1, present the methods used to collect and incorporate a preliminary sample of expert knowledge, then explore the properties of scenarios that may be specified from this network model.

The structure of the network was developed over multiple iterations where the study team, colleagues and others with CCS experience and expertise considered interactions among individual variables as well as the overall structure and interactions among components of the network. The resulting CCS BBN includes two primary subsections, the left portion representing technology and cost factors that eventually feed into node 12 Cost Competitiveness, and the right portion addressing socioeconomic and political issues that eventually influence node 34 Likelihood of Planning Approval. These summary nodes then determine the distribution of node 35 Deployment Rate. Node 36 indicates whether node 35 is H or VH, allowing the network to be constrained to scenarios where the level of deployment is at least H. Participants in the survey described below were told that the period for possible deployment represented in our analysis ranged from the present until 2050.

Overall there are a total of 36 nodes in the network, including 17 top (root) nodes defined initially by the prior probabilities for their states. These include nodes 1–5 in the technology-cost portion of the network and nodes 13–24 in the socioeconomic-political section. In addition, there are 19 downstream (child) nodes that are influenced by one or more parent node (in many cases these child nodes also serve as parents for subsequent downstream variables). In all cases a parent and a child are connected by an arrow indicating the direction of influence. While many of the technical-cost variables can be derived from quantitative analysis, most of social variables are qualitative in nature. Examples include:

- Regulatory Clarity: the extent to which environmental and energy authorities have provided clear and appropriate regulations, rules, and enforcement capacity to enable industry developers and stakeholders to understand what is expected to build and operate a safe CCS system.
- Local Political Support: the extent to which local government is supportive of and collaborates which CCS development, promoting



(caption on next page)

Fig. 2. Scenario 2. Fully pessimistic assumptions for both technology and policy variables.

citizen education and input from its constituencies.
- Outcome Efficacy: The extent to which citizens and stakeholder groups can be assured that their concerns and preferences are given serious weight in informing CCS construction and operational decisions.

To implement the influence of these and other variables in the model, the joint influence of multiple parents on a child is characterized by the child's conditional probability table (CPT). Note that for most of the nodes in the network, values closer to VL (=0.1) are associated with a pessimistic view towards CCS deployment, while values closer to VH (=0.9) denote optimism towards CCS. In some cases, however, the order is reversed. These variables include: the cost-related nodes 2, 5, 6, 7, 8, 9, 10, and 30 (higher costs lead to lower cost competitiveness in node 12 and therefore lower probabilities of deployment in node 35); as well as selected social-environmental variables: national public support for alternatives such as wind or solar (node 13), local activism (node 16), land use competition (node 17), environmental risk (20), and perceived risk (32), since higher values of these lead to lower the likelihood of planning approval in node 34 and therefore lower expectations regarding deployment in node 35.

While the technical-cost and socioeconomic/political aspects of the model are generally assumed to act independently (until they are aggregated through nodes 12 and 34 to predict the deployment level in node 35), the network does include a number of important technical-social cross influences. In particular, node 25 National Political Support is indicated to influence node 13 Strength of Subsidies (making larger subsidies more likely), while node 12 Cost Competitiveness exerts influence on node 30 Perceived Cost (lower cost competitiveness results in higher perceived costs, which in turn results in higher perceived risk in node 32). While other relationships among technical and social variables might be considered for inclusion in the network, the difficulties in framing and estimating their causal influence, and the very low number of studies upon which this can be based, argue in favor of limiting their number in this initial demonstration of the methodology.

2.2.2. *Estimating model probabilities*

Prior (top node) and conditional probabilities (i.e., the CPTs) are estimated for the network using the following steps:

1 A sample of four general CCS experts from academia and industry located in the Oceania regionT was elicited for their weightings (as a percent, summing to 100) of the relative importance of each parent to each child node in the network.[1] The weights for each expert are shown in Appendix A, along with the averages of these weights which are used to derive the initial conditional probability table for each child node, using the logistic normal approximation method described in Appendix B. Note that for child nodes with a large number (n_p) of parents, the number of rows in the CPT ($=5^{np}$) is very large. The logistic normal method for CPT estimation does have limitations (e.g., it does not consider synergy among the parent nodes in their effects upon the child), however, it does provide a novel, feasible basis for estimating large CPTs without imposing a difficult or impossible burden on the elicited experts, as is often encountered with available methods (see Appendix B references).

2 An online-email survey was conducted asking experts from different parts of the world to indicate the most likely state for the nodes in the network. The elicitation process involved identifying a diverse collection of people working in a field related to CCS and surveying their perceptions on the various techno-economic and socio-political variables identified in existing literature and included in the network model. International CCS professionals with a variety of roles and disciplinary backgrounds were identified through personal contacts and key personnel involved in previously delivered projects. Respondents indicated a range of experience, with most reporting they had 10–15 (41.7%) or 5–10 (27.1%) years in a field related to CCS. The remainder of respondents had 15+ (18.8%), or 2–5 (10.4%) years of experience, with only one respondent indicating less than 2. Additionally, the background of respondents was split fairly evenly amongst academia (25.0%), engineering (29.2%), policy planning (20.8%), and project management (25.0%).

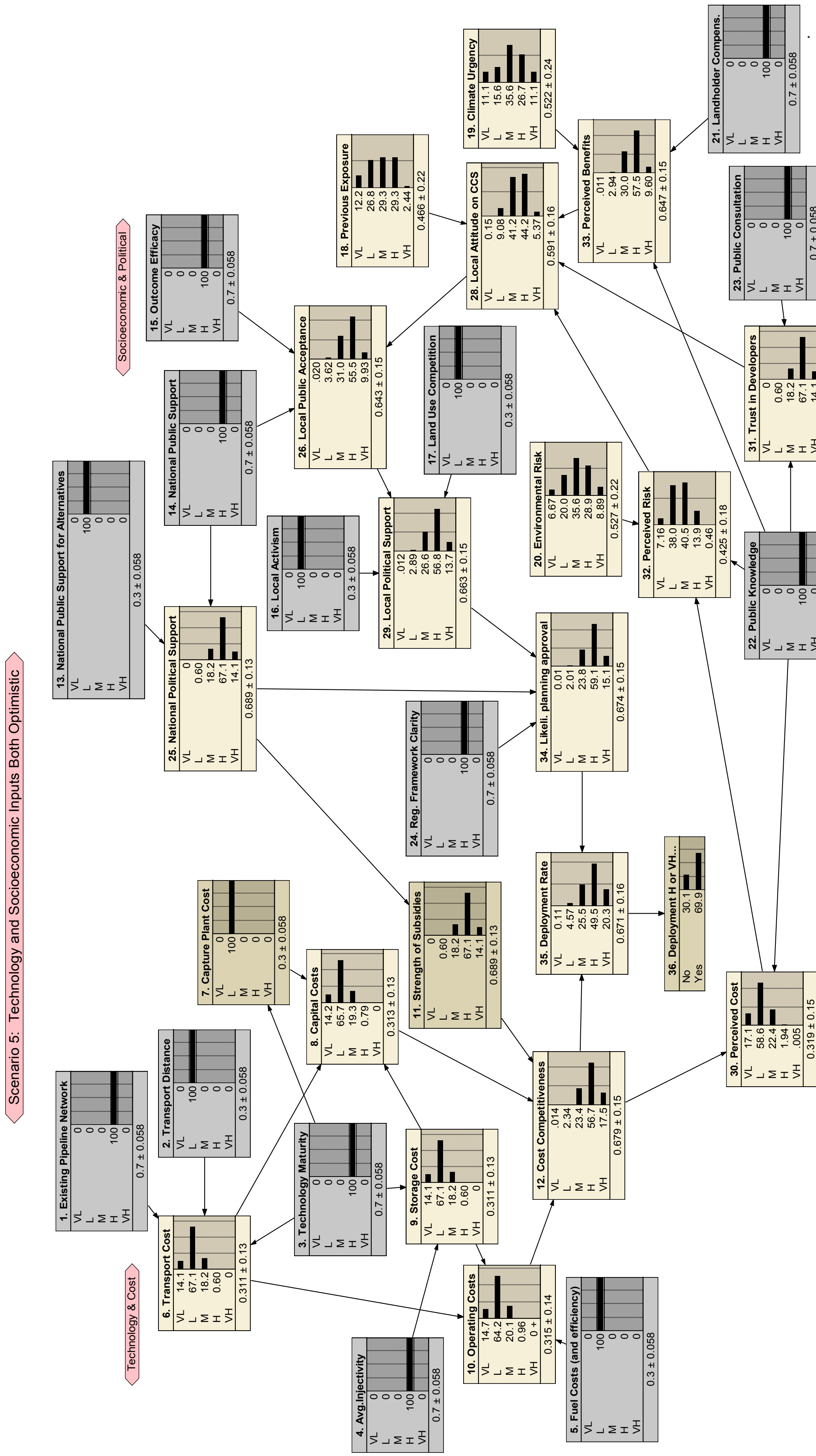
Respondents were invited to complete the survey via an online link emailed to them, and were also asked to forward the link to those they considered relevant people in order to increase the potential respondents. Responses from the survey were collected from a total of 51 respondents in 5 separate regions over a four week period from the 13th of February to the 13th of March 2017. This number was reduced to 42 when accounting for participants who answered less than 10% of the survey. The experts were asked to identify the most likely state for each variable in the network model. The answers for each expert correspond to a "case" for the BBN. These cases were then used with the Netica "learning from cases" option based on the EM algorithm (Neapolitan, 2004) to update the top node probabilities and child node CPTs[47]. As with the first expert elicitation that was used to provide a preliminary set of CPT estimates (described above in 1), the results of this email survey and their use to learn from cases is primarily to illustrate the overall methodology, and more extensive expert elicitations are needed to yield more representative results and allow for reliable comparisons across groups of experts.

The fitted network in Fig. 1 includes the marginal probability of all states for all nodes, as informed by the expert input. Not shown are the CPTs for each child node (informed by both the expert weights and the survey results), which play a fundamental role in the model predictions. As noted above, some of the CPTs are quite large. To illustrate the structure and content of the fitted CPTs, examples are presented for Node 6 Transport Cost and Node 33 Perceived Benefits in Appendix C.

3. Results and inferences from fitted BBN

As indicated for the fitted network in Fig. 1, many of the nodes in the expert BBN exhibit a high degree of uncertainty, and most of the variables are skewed towards a more pessimistic view of the conditions influencing rapid deployment of CCS, with mean values below (above) 0.5 for those variables where increasing (decreasing) values result in a greater chance of CCS deployment. The collective expert judgment yields optimistic distributions (with mean values on the optimistic side of 0.5 for that variable) for only six of the model variables: transport distance (node 2, mean = 0.421); average injectivity (node 4, mean = 0.587); fuel costs (node 5, mean = 0.265); storage cost (node 9, mean = 0.429); operating cost (node 10, mean = 0.378); and the level of land use competition (node 17. Mean = 0.373). As a result, the summary Cost Competitiveness variable (node 12) is slightly pessimistic (mean = 0.487), the Likelihood of Planning Approval (node 34) is decidedly pessimistic (mean = 0.367), and the overall summary variable, Deployment Rate (node 35) is moderately pessimistic (mean = 0.453). The fitted model thus expresses an aggregate expert view that, while the technology and cost elements of the model are nearly balanced between optimism and pessimism, the concerns and doubts related to the socioeconomic and political dimensions of CCS

[1] The purpose of this study is to serve as a proof of concept. A larger pool of experts is needed to establish a more confident estimate of expert-averaged beliefs and to provide a basis for assessing differences across experts [48,49].



(caption on next page)

Fig. 3. Scenario 5 Fully optimistic for both technology and social inputs.

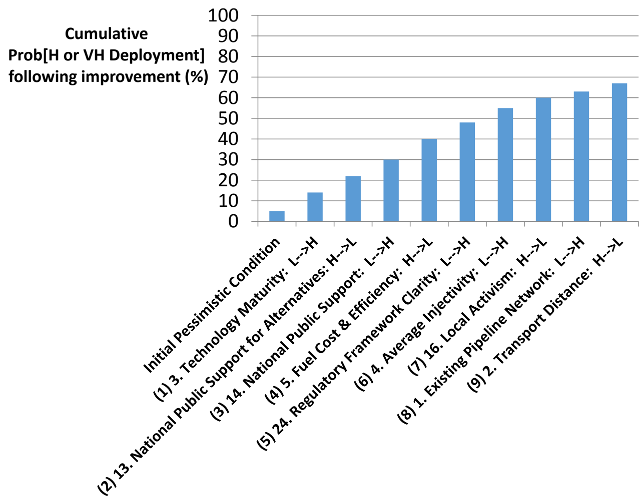


Fig. 4. Cumulative effect of sequentially improving model factors beginning with the fully pessimistic scenario. (Factors chosen so that the Prob[H or VH Deployment] is predicted to increase maximally at each step.)

result in an expert model which predicts a low (~21 percent) chance of H or VH deployment (see node 36).

3.1. Exploration of scenarios

The network in Fig. 1 represents an expert-informed baseline scenario for CCS deployment. Further scenarios can be derived by specifying values or ranges of values (with associated probabilities) for one or more of the nodes in the network. If particular states are chosen for some nodes, but not others, the probabilities for the latter (unspecified) node states are recalculated by the network model using Bayes Rule to yield an updated, posterior network.

To illustrate the specification of scenarios, the calculation of distributions for key output variables for each, and the simulation of specific cases for a given scenario, we begin with the fitted network in Fig. 1 which serves as the baseline model scenario. We then systematically set groups of technology or and/social nodes to high (H) or low (L) levels to represent different levels of optimism. Table 1 lists the baseline and the four new scenarios, the five upstream technology and cost nodes and the nine socioeconomic and political nodes that are set to either L or H to represent plausible levels of overall pessimism or optimism for each scenario (Note that the L, H settings are reversed for those variables where lower values promote CCS deployment and higher values impede the deployment, as indicated in the table). Fig. 2 shows the updated network for the fully pessimistic assumptions, representing Scenario 2, while Fig. 3 shows the updated network for the fully optimistic case of Scenario 5. Corresponding network diagrams for the mixed Scenarios 3 and 4 are presented in Appendix D of the Supporting Information.

Shown in Table 1 are eight representative output nodes and their computed mean values, including: 8. Capital Cost; 10. Operating Cost; 11. Strength of Subsidies; 29. Local Political Support; 32. Perceived Risk; 33. Perceived Benefits; and 36. Deployment H or VH? (for three of these variables: 8. Capital Cost, 10. Operating Cost, and 32. Perceived Risk; a lower value, closer to 0, is more supportive of CCS deployment than a value that is higher and closer to 1). As indicated, the predicted probability of high or very high CCS deployment (last column in Table 1) varies widely over the range of pessimistic to optimistic technical and social input assumptions for the model. Beginning with the baseline Scenario 1, where the probability of H or VH CCS deployment is predicted to be 21 percent, the assumption of fully pessimistic technical and social inputs (shown in Fig. 2), causes this probability to decrease to only 5 percent. When one set of inputs (technical or social) is assigned an optimistic value while the other set is pessimistic, small improvements are made in the probability of H or VH adoption relative to the baseline scenario, with the probability increasing from 21 to 24 percent when the social dimensions are optimistic and from 21 to 32 percent when the technical dimensions are optimistic. In contrast, when both aspects are assigned optimistic values as shown in Fig. 3 for Scenario 5, the probability of H or VH deployment increases substantially to 70 percent. This result is due in part to the fact that Scenario 1 begins with relatively pessimistic baseline specifications (as derived from the expert elicitation), but is also consistent with the proposition that a high probability of success for CCS deployment is dependent on substantial improvements in both the technological and socioeconomic spheres. Improvements in only one of these domains is thus not expected to yield successful penetration.

In addition to the probability of H or VH CCS deployment, the six other selected outputs in Table 1 indicate variable responses to the pessimistic, optimistic and mixed scenarios. Compared to the expert-informed prior model, the fully pessimistic Scenario 2 results in significantly worse mean values for Capital Cost, Operating Cost, Local Political Support and Perceived Risk, though much smaller changes for Strength of Subsidies and Perceived Benefits. These latter two variables are thus indicated to be less responsive to imposition of more pessimistic assumptions than are the cost, political support and perceived risk variables. The optimistic Scenario 5 yields large improvements across all of the selected outputs, in part because their initial (Scenario 1) mean values were largely pessimistic to begin with. The mixed scenarios yield shifts in output nodes of varying direction and magnitude, depending on whether these factors are located within (and thus most affected by) the technical or social portions of the network model.

3.2. Sequential improvement of factors to raise likelihood of deployment

As shown in Table 1 and Figs. 2 and 3, the probability of H or VH deployment does improve significantly when a high proportion of influencing factors achieve a high level of performance. This leads to the question, are certain factors more important than others? Are some factors or groups of factors critical, so that their improvement provides a strong, perhaps even necessary precursor to CCS deployment?

To identify potentially critical factors we begin with the fully pessimistic scenario in Fig. 2 and sequentially improve the performance of factors from pessimistic to optimistic, one at a time, choosing at each step the factor that most increases the probability of H or VH CCS deployment. The candidate factors include those listed in Table 1:

> Technical: 1. Existing Pipeline Network, 2. Transport Distancec, 3. Technology Maturity, 4. Avg. Injectivity, 5. Fuel Costs (and efficiency)
> Social: 13. National Public Support for Alternatives, 14. National Public Support (for CCS), 15. Outcome Efficacy, 16. Local Activism, 17. Land Use Competition, 21. Landowner Compensation 22. Public Knowledge, 23. Public Consultation, 24. Regulatory Framework Clarity

Results for this analysis are summarized Fig. 4. The nine improvements in model factors from pessimistic to optimistic increase the predicted probability of achieving H or VH deployment from 5 percent to 67 percent. The nine variables that contribute to the markedly improved conditions for CCS adoption include five technology-cost

factors: Technological Maturity; Fuel Cost & Efficiency; Average Injectivity; Existing Pipeline Network; and Transport Distance; and four social-regulatory variables: National Public Support for Alternatives; National Public Support; Regulatory Framework Clarity; and Local Activism. Improvements in Technology Maturity (i.e., technological readiness) is the first, most influential variable contributing to the predicted increase in CCS deployment likelihood. It has a direct influence on other important variables in the network, including Capture Plant Cost, Transport Cost, and Storage Cost, yielding secondary influences on Capital Costs and Operating Costs.

The next two input factors with high influence are the social factors: National Public Support for Alternatives and National Public Support for CCS. These factors clearly reflect public opinion – and subsequently private and public sector support, for continued use of fossil or biofuels with CCS, versus accelerated adoption of renewable alternatives. This is reflected in the network through their joint impact on National Political Support, the impact of National Public Support on Local Public Acceptance, and their secondary influence on Local Political Support, Strength of Subsidies, and Likelihood of Planning Approval. The third social-political variable with high importance for improved conditions for CCS deployment is Regulatory Framework Clarity. As uncertainty persists regarding the contribution of CCS to national plans for carbon reduction, as well as the requirements and regulatory capacity needed to ensure proper and safe siting, operations, containment and eventual closure, the need for industry to anticipate a stable regulatory environment remains critically important.

While one could envision the sequence of improvements in Fig. 4 as possibly representative of a particular scenario of improvement and likely CCS adoption over time, the chance of this particular realization (along with a meaningful prediction of the timing of each improvement) is quite low. But so is every other specific case for the temporal evolution of the network variables. Instead the coevolution of different factors can be structured as an (uncertain) outcome of different Shared Socioeconomic Pathways. This would allow the network model for CCS, and subsequently other emerging energy technologies with significant technical and social dimensions, to be linked with ongoing SSP simulations and applications. In this context Bayesian network models can serve as a flexible platform for considering portfolios of energy system technologies and transitions, in conjunction with different sets of technical, cost, and social outcomes specific to each.

4. Concluding discussion

The model and illustrative application presented in this paper demonstrate a flexible framework for deriving a set of linked technical-socioeconomic scenarios to predict the likelihood of significant deployment for emerging energy technologies. The approach uses a Bayesian network that identifies and integrates the technical maturity, cost, environmental, socioeconomic, risk perception, and political factors that together promote or limit the pace and extent of a transition to a new energy technology. The variables in the network model include both qualitative and quantitative factors that influence each other through conditional probability relationships informed by expert judgment and elicitation.

Two approaches for expert elicitation in conjunction with a Bayesian network model are demonstrated: i) eliciting from experts their relative weights as to the importance of each parent node influencing each child node; and ii) asking multiple experts to choose the most likely state for each variable in the network, using each expert's selections as a case in a learning from cases algorithm that updates the root node and conditional probabilities in the model. While the methods yielded informative (and very plausible) relationships, neither the sample sizes nor the methods for choosing and validating expert judgments are considered fully sufficient for drawing strong inferences at this stage. Further elicitation for this and other emerging energy technologies is planned.

The methodology is demonstrated by development and application of a Bayesian network model for CCS deployment. The baseline expert-informated model is generally pessimistic for most of the individual upstream factors in the model as well as for the resulting predicted probability of high or very high deployment (about 20 percent). However, significant improvement or reduction in this baseline likelihood of adoption is inferred when combinations of upstream factors are modified. Four scenarios are considered. When all of the influential technical and social factors are assigned pessimistic values, the probability of high or very high deployment of CCS drops to a low value of 5 percent. In contrast, when all of the influential technical and social factors are set to optimistic values, the probability of high or very high adoption increases to 70 percent. These estimates represent an initial assessment of the range of probabilities for CCS adoption. Intermediate scenarios with pessimistic technical assumptions and optimistic social assumptions (or vice-versa) yield only small improvements in the predicted likehood of adoption relative to the baseline, from 20 percent to between 25 and 32 percent. The network model thus suggests that technical and social factors exhibit some degree of synergy, and that improvements to *both* are needed to enable a high likelihood of success.

A further set of scenarios is constructed by modifying the baseline network by sequentially improving individual factors, choosing at each increment the factor that most improves the cumulative probability of high or very high deployment. Nine factors are identified, five technical-cost variables: Technological Maturity; Fuel Cost & Efficiency; Average Injectivity; Existing Pipeline Network; and Transport Distance; and four social-regulatory variables: National Public Support for Alternatives; National Public Support; Regulatory Framework Clarity; and Local Activism. Improvements in these together improve the predicted probability of deployment to 67 percent (nearly equal to the 70 percent value achieved in the fully optimistic scenario. Further study and modeling of these model components and processes is inferred to be of high priority. A highly interdisciplinary portfolio of research is clearly needed to advance our understanding of these dimensions, and their interactions.

The development and application scenarios for exploration of possible economic, energy, emissions, and climate impacts has made much progress in recent years, though many challenges remain. It remains difficult to link processes across technical and social domains, quantitative and qualitative variables, and with sources of knowledge that include physical measurements, multiple model predictions, and expert input from individuals and groups that both influence assessments and learn from them. Consideration of a range of methods for scenario development, aided by tools such as the expert-informed network developed in this paper, can help to facilitate exploration of the critical processes, variables, interactions, and uncertainties that will affect future outcomes.

Acknowledgment

This research was supported primarily by the Dow Centre for Sustainable Engineering Innovation at The University of Queensland. Additional support was provided by the Anderson Family Visiting Professorship in Energy and the Environment in the Department of Civil and Environmental Engineering and the Andlinger Center for Energy and the Environment, Princeton University, and the H. John Heinz III Professorship of Environmental Engineering at Carnegie Mellon University. Helpful discussions of the approach and focus were provided by Peta Ashworth, Eric Larson, Fabian Wagner and Natasha Turkmani.

Appendix A. Expert elicited weights for the relative influence of parent nodes on each child node. Direction of influence indicated as + (positive) or − (negative)

Child Node	Parent Nodes	Direction of influence	Expert number 1	2	3	4	Average weight
35 Deployment rate	12 Cost competitiveness	+	60%	80%	60%	80%	70%
	34 Likelihood of planning approval	+	40%	20%	40%	20%	30%
34 Likelihood planning approval	24 Regulatory framework clarity	+	25%	30%	50%	20%	31%
	29 Local political support	+	45%	35%	25%	40%	36%
	25 National political support	+	30%	35%	25%	40%	33%
29 Local political support	17 Land use competition	–	30%	20%	20%	10%	20%
	16 Local activism	–	30%	30%	30%	20%	28%
	26 Local public acceptance	+	40%	50%	50%	70%	53%
26 Local public acceptance	14 National public support	+	30%	20%	20%	20%	23%
	15 Outcome efficacy (belief of influence over outcome)	+	30%	40%	20%	40%	33%
	28 Local attitude on CCS	+	40%	40%	60%	40%	45%
28 Local attitude on CCS	32 Perceived risk	–	20%	30%	35%	50%	34%
	33 Perceived benefits	+	20%	40%	20%	10%	23%
	18 Previous exposure to industry	+	30%	15%	15%	20%	20%
	31 Trust in developers	+	30%	15%	30%	20%	24%
18 Perceived risk	30 Perceived cost	+	20%	20%	30%	10%	20%
	22 Public knowledge	–	40%	30%	20%	20%	28%
	20 Perceived environmental risk	+	40%	50%	50%	70%	53%
30 Perceived costs	12 Cost competitiveness	–	60%	30%	50%	50%	48%
	22 Public knowledge	–	40%	70%	50%	50%	53%
33 Perceived benefits	21 Landholder compensation	+	40%	80%	50%	40%	53%
	19 Climate urgency	+	30%	10%	20%	40%	25%
	22 Public knowledge	+	30%	10%	30%	20%	23%
31 Trust in developers	22 Public knowledge	+	50%	30%	20%	20%	30%
	23 Public consultation	+	50%	70%	80%	80%	70%
25 National political support	13 National public support for alternatives	–	50%	50%	40%	90%	58%
	14 National public support	+	50%	50%	60%	10%	43%
12 Cost competitiveness	10 Operating costs	−	25%	30%	20%	40%	29%
	11 Strength of subsidies	+	25%	20%	20%	20%	21%
	8 Capital costs	−	50%	50%	60%	40%	50%
8 Capital costs	9 Storage cost	+	25%	10%	15%	10%	15%
	6 Transport cost	+	25%	10%	15%	10%	15%
	7 Capture plant cost	+	50%	80%	70%	80%	70%
10 Operating costs	6 Transport cost	+	30%	20%	20%	10%	20%
	5 Fuel cost (and efficiency)	+	35%	60%	50%	80%	56%
	9 Storage cost	+	35%	20%	30%	10%	24%
6 Transport cost	1 Existing pipeline network	−	40%	40%	45%	50%	44%
	2 Transport distance	+	50%	50%	45%	50%	49%
	3 Technological maturity	−	10%	10%	10%	0%	7.5%
9 Storage cost	4 Average injectivity	−	80%	90%	80%	90%	85%
	3 Technological maturity	−	20%	10%	20%	10%	15%

Appendix B. A logistic normal allocation method for CPT elicitation

Bayesian Belief Networks (BBNs) provide a powerful means for propagating influence between related events and outcomes. However, estimating the conditional probability tables (CPTs) that relate a downstream (child) node to its upstream parents can be very difficult, especially when two or more parent nodes with multiple states influence the child. While mechanistic models or equations can sometimes be used for this purpose, and "learning from cases" may in some instances be employed (especially when many diverse cases are available), a common method for constructing CPTs is based on expert elicitation.

Multiple approaches have been proposed for conducting expert elicitations for a BBN (Druzdzel and Van Der Gaag, 1995; Renooij, 2001; Fenton et al., 2007; Laitila and Virtanen, 2016; Mkrtchyan et al., 2016). The most direct and complete approach is to ask the expert their assessment of the probability of each state in the downstream node given each combination of states in the upstream nodes. So, for example, if there are three upstream nodes, each with five states, and the downstream node likewise has five states, then there are $5 \times 5 \times 5 = 125$ rows in the CPT (one for each combination of states in the upstream nodes) and 5 columns, one for each state in the downstream node. Since the probabilities of each of the states in a row must sum to one, the probability of the fifth downstream state is determined from that of the other four. There are thus $125 \times 4 = 500$ probabilities that must be elicited. Even if an expert is willing to be probed for the amount of time needed to generate these estimates (and perhaps for many more probability values for the other nodes in the model), it would be very difficult for them to ensure that their entries are self-consistent in terms of the relative influence of the upstream states and their combinations.

This paper introduces and applies an approximate, first-order method for eliciting a CPT for a BBN node given a minimal quantity of information elicited from the expert: (i) a weight assigned to each upstream node reflecting their relative strength of influence on the downstream node; and (ii) the level of confidence that the expert has in this assessment. A third set of quantities may also be elicited from the expert to allow them to scale and center their assessment of the downstream node state probabilities. This option is discussed further at the end of this appendix, but not used for the CPT calculations in this paper.

The method is illustrated for a case where all three upstream nodes and the downstream node have five states: very low (VL); low (L); medium (M); high (H); and very high (VH), similar to that of a Likert scale with five options. On the continuous scale from 0 to 1, VL is associated with the

interval 0–0.2, L with 0.2–0.4, M with 0.4–0.6, H with 0.6–0.8, and VH with 0.8–1.0. The states are assigned the midpoint value of each range, with VL = 0.1, L = 0.3, M = 0.5, H = 0.7, and VH = 0.9. When node i is serves as a parent node for one or more children, these scores are referred to as Z_i. The influence of each parent node on the child node is assumed to be monotonic and proportional to the parent node score, but is modified to account for the direction of influence of the parent upon the child. When the parent-child influence is positive, the parent's influence score on node j is the same as it's raw score, $X_{i,j} = Z_i$. When the parent-child influence is negative, the parent's influence score on node j is modified to $X_{i,j} = 1 - Z_i$. The weights assigned for the relative importance of each parent, $w_{i,j}$, (e.g., by expert judgment) are then used to calculate the median score for the given row of the CPT (in which $X_{i,j}$ is specified for each parent):

$$X_{50,j} = \sum_{i=1}^{nj} w_{i,j} X_{i,j} \tag{B1-1}$$

where $X_{50,\,j}$ is the median score for child node j; n_j is the number of parent nodes for child node j; $X_{i,\,j}$ is the influence score of parent node i for child node j (for the particular row of the CPT); and $w_{i,j}$ is the weight assigned to parent node i for its influence on child node j. The weights range from 0 to 1, and they must sum to 1:

$$\sum_{i=1}^{nj} w_{i,j} = 1.0 \tag{B1-2}$$

Once the median score is computed for child j, a probability distribution of its score (between 0 and 1) is needed to allocate the conditional probability across the intervals corresponding to each state of the child node. A logistic normal distribution is assumed for this purpose. If the node j score, X_j, follows a logistic normal distribution, then

$$Y_j = \text{logit}(X_j) = \ln\left[\frac{X_j}{1 - X_j}\right] \quad \sim \quad \text{Normal } [\mu_{\text{Yj}} = \text{Y}_{50,\text{j}}, \sigma] \tag{B1-3}$$

The logistic normal variable X_j can be calculated from the normal variable Y_j using the inverse logit equation:

$$X_j = \text{inv logit} \quad = \left[\frac{1}{1 + \exp(Y_j)X_j}\right] \tag{B1-4}$$

With the normal designation for the logit variable Y_j, its median $Y_{50,\,j}$ is equal to its mean μ_{Yj}, and this value (calculated in Eq. (B1-1)) is the first parameter of the logistic normal distribution.

The second parameter σ is the standard deviation of the logit variable. This value should be reflective of the level of confidence or surety that the expert has that the probability distributions for X_j and Y_j are tightly distributed around their median values, $X_{50,j}$ and $Y_{50,j}$, as these provide the expert's point estimate for the child node. When the expert is highly confident in their upstream weights and believes that the conditional probabilities for each row of the CPT are tightly distributed around the predicted median for that row, then a small value of σ is appropriate, concentrating the conditional probability of X_j near its median for the given row. When the expert is very uncertain about their upstream weights and believes that the distribution of conditional probabilities around the median for each row of the CPT is more widely dispersed, a larger value of σ is appropriate. This results in a less concentrated, more uniform spread of the conditional probability of X_j over the range (0, 1) and a more uniform distribution of probability across the corresponding states of the child node. In this study we assigned values of σ corresponding to three levels of confidence: high confidence, σ = 0.5; medium confidence, σ = 1.05; low confidence, σ = 1.6. The implications of these choices are illustrated in the example that follows.

The final step in the method is to allocate the proper conditional probability to each state of the child node based on the probability that X_j falls within the interval assigned to that state, or equivalently that Y_j falls within its interval for each state, based on its normal distribution. This is computed as the cdf of the upper value of the interval for the state, minus the cdf of the lower value of the interval. So, for a 5-state (Likert scale) child node with the following states and intervals, the calculation proceeds as shown in Table B1. As indicated the cdf of either X_j or Y_j can be used for this purpose, though evaluation of the normal cdf is easier (and most programs for computing the logistic normal cdf convert the variable to the normal equivalent in any case).

Table B1
Discretization of logistic normal variable, X_j for a 5-state Likert scale, and corresponding intervals of the normal variable, Y_j. Calculation of the probability of each state is given by the cdf equations in the final column, with equivalent results obtained using either the X_j cdf or the Y_j cdf. For the latter the mean = median of Y_j is calculated using Equation B1-1 and the standard deviation is chosen based on the expert's level of confidence.

State	X_j mid-point	X_j interval	Y_j interval	Prob[State i]
1 VL	0.1	0–0.2	< -1.386	$= F_{Xj}(0.2) = F_{Yj}(-1.386)$
2 L	0.3	0.2–0.4	-1.386 - -0.405	$= F_{Xj}(0.4)–F_{Xj}(0.2) = F_{Yj}(-0.405)–F_{Yj}(-1.386)$
3 M	0.5	0.4–0.6	-0.405–0.405	$= F_{Xj}(0.6)–F_{Xj}(0.4) = F_{Yj}(0.405)–F_{Yj}(-0.405)$
4H	0.7	0.6–0.8	0.405–1.386	$= F_{Xj}(0.8)–F_{Xj}(0.6) = F_{Yj}(1.386)–F_{Yj}(0.405)$
5 VH	0.9	0.8–1	> 1.386	$= 1–F_{Xj}(0.8) = 1–F_{Yj}(1.386)$

B.1. Example application

To illustrate the behavior of the logistic normal expert elicitation method, the following BBN is implemented in Netica. As shown the three parent variables: A, B and C; exert some degree of influence on the child variable, D. In the prior network shown in Fig. B1 all prior probabilities of the parents are uniform (20% assigned to each state of the parent node). Similarly, each row of the CPT for D is uniform. This results in the computed uniform prior distribution shown for D.

The first 10 rows of the prior CPT for node D are presented in Table B2. As indicated all entries are the same (20 percent), as is the case for the

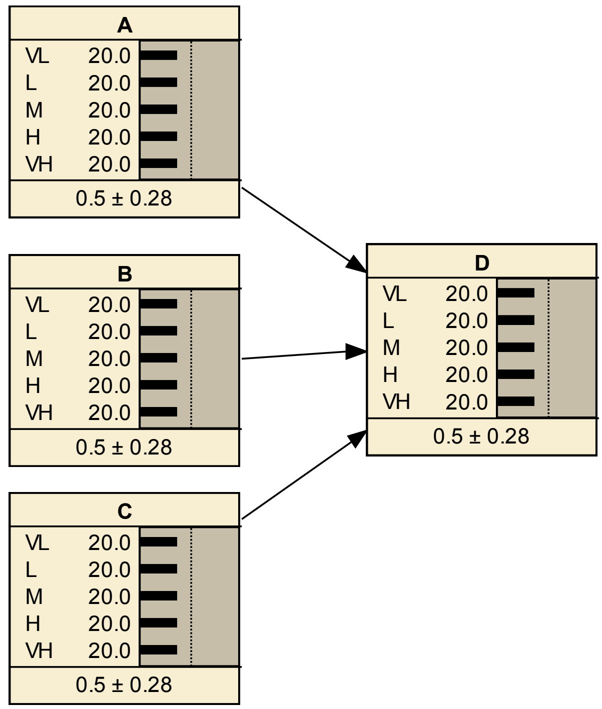


Fig. B1. Prior BBN for influence of parent nodes A, B and C on child node D. All prior and conditional probabilities are assumed uniform (=20%). For all nodes the values associated with each state are VL = 0.1; L = 0.3; M = 0.5; H = 0.7; and VH = 0.9, and the box at the bottom of each node shows its computed mean and standard deviation.

Table B2
Assumed conditional probability table for node D under uniform prior. Only the first 10 cases are shown, the entries for the remaining 115 rows are identical (all entries = 20 percent).

Parent node state				For node D, the assumed prior probability of:				
Case	A	B	C	VL = 0.1	L = 0.3	M = 0.3	H = 0.7	VH = 0.9
1	0.1	0.1	0.1	20.000	20.000	20.000	20.000	20.000
2	0.1	0.1	0.3	20.000	20.000	20.000	20.000	20.000
3	0.1	0.1	0.5	20.000	20.000	20.000	20.000	20.000
4	0.1	0.1	0.7	20.000	20.000	20.000	20.000	20.000
5	0.1	0.1	0.9	20.000	20.000	20.000	20.000	20.000
6	0.1	0.3	0.1	20.000	20.000	20.000	20.000	20.000
7	0.1	0.3	0.3	20.000	20.000	20.000	20.000	20.000
8	0.1	0.3	0.5	20.000	20.000	20.000	20.000	20.000
9	0.1	0.3	0.7	20.000	20.000	20.000	20.000	20.000
10	0.1	0.3	0.9	20.000	20.000	20.000	20.000	20.000

remaining 115 rows of the CPT. This CPT characterizes an overall prior relationship for the influence of A, B and C on D that is flat and uniformed.

To update the CPT based on elicited expert judgment, we now illustrate how different initial weights for the parents and different levels of confidence expressed by an expert affect the CPT and the predicted probabilities for the states in node D. Fig. B2 takes the BBN in Fig. B1 and fits its CPT for four cases: equal weights for A, B and C with the low and high confidence cases described above (with $\sigma = 1.6$ and 0.5, respectively); and with unequal weights (A = 0.7, B = 0.2, and C = 0.1), again with the low and high confidence cases described above. In Fig. B2 the four networks have been updated with the CPTs for node D corresponding to each of the four cases of expert judgment, however, no evidence has as yet been entered for the upstream nodes. As indicated, the expert informed network (with no states specified) for the cases with low confidence (sigma = 1.6), with either equal weighting or differential weighting, yield similar, very flat priors for D. With high expert confidence (sigma = 0.5) the equal and differential weighting results are also similar, though the probability for D is drawn in toward the mid-range states of M, L and H.

Fig. B3 displays results for the four cases when the upstream A node is determined to be in state VH, but nodes B and C are unspecified. In all four cases the probabilities for downstream node D shift upward toward VH, with the lowest shift occurring for the case of Equal Weights and Low Confidence, and the largest shift occurring with unequal weights (in particular, with the weight for A = 0.7) and high confidence.

The effect of another upstream assignment is illustrated in Fig. B4. There the case in Fig. B3 (A assigned VH, with B and C unspecified) is modified by assigning B and C to states VL, so that they apply an opposite influence on node D compared to that applied by node A. As shown, for the cases with equal weights, the probabilities for node D are now shifted downward given the evidence, more so when the expert expresses high confidence. Since all three upstream nodes have the same weight, the two VL assignments to B and C are enough to more than override the VH assignment to A. However, in the bottom portion of Fig. B4, the greater weight assigned to A (0.7) vs. B and C (0.2 and 0.1, respectively) is such that a net shift in probability to the higher states in node D still results, despite the VL assignments made to B and C.

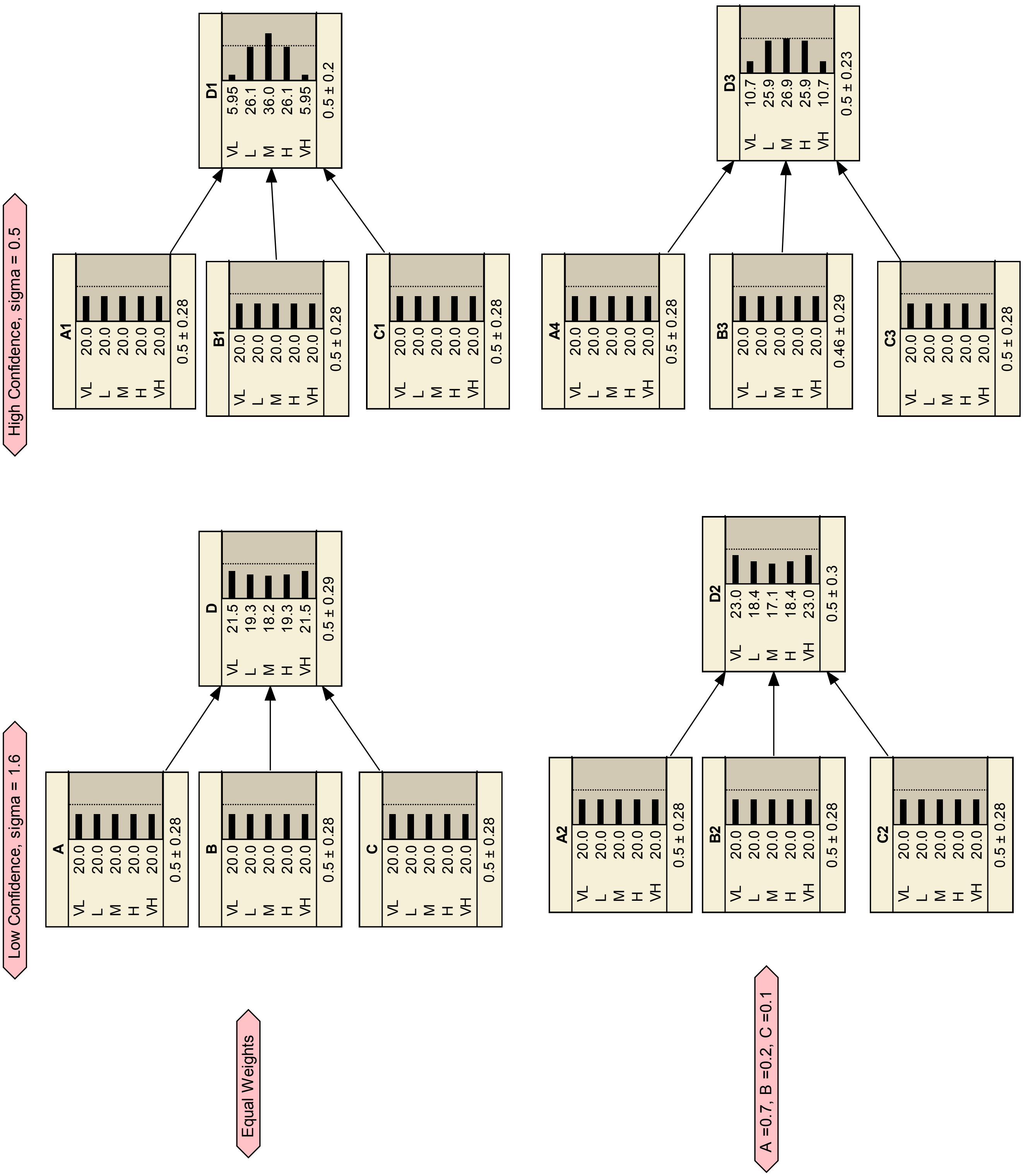


Fig. B2. Expert informed BBN for the four cases considered, but with no upstream states specified for A, B or C. Note: in this and the figures that follow, the CPT has been calibrated using the indicated weights and level of confidence.

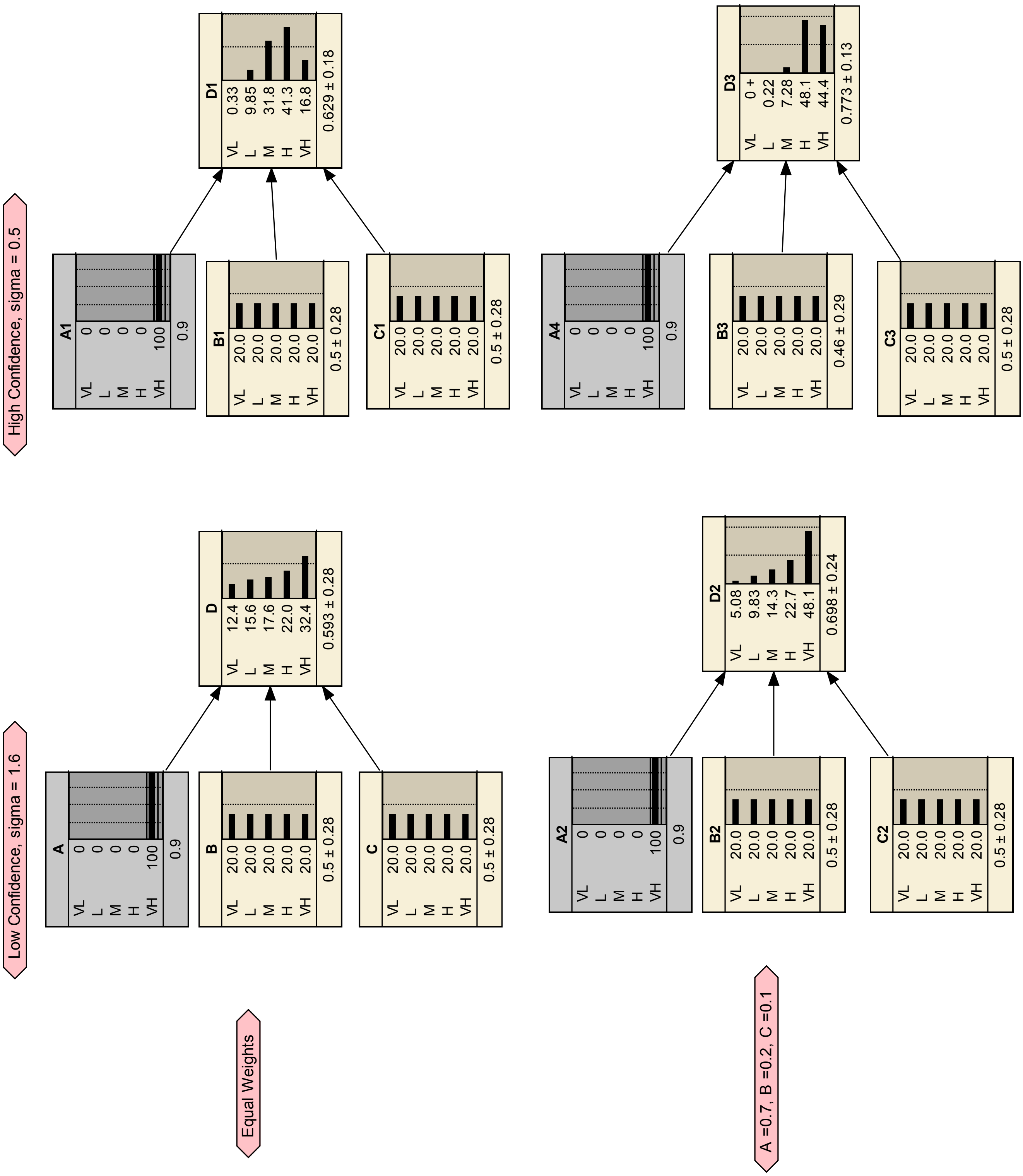


Fig. B3. Posterior BBN when evidence is entered for A (= VH), but the other upstream nodes are unspecified, for the four cases considered.

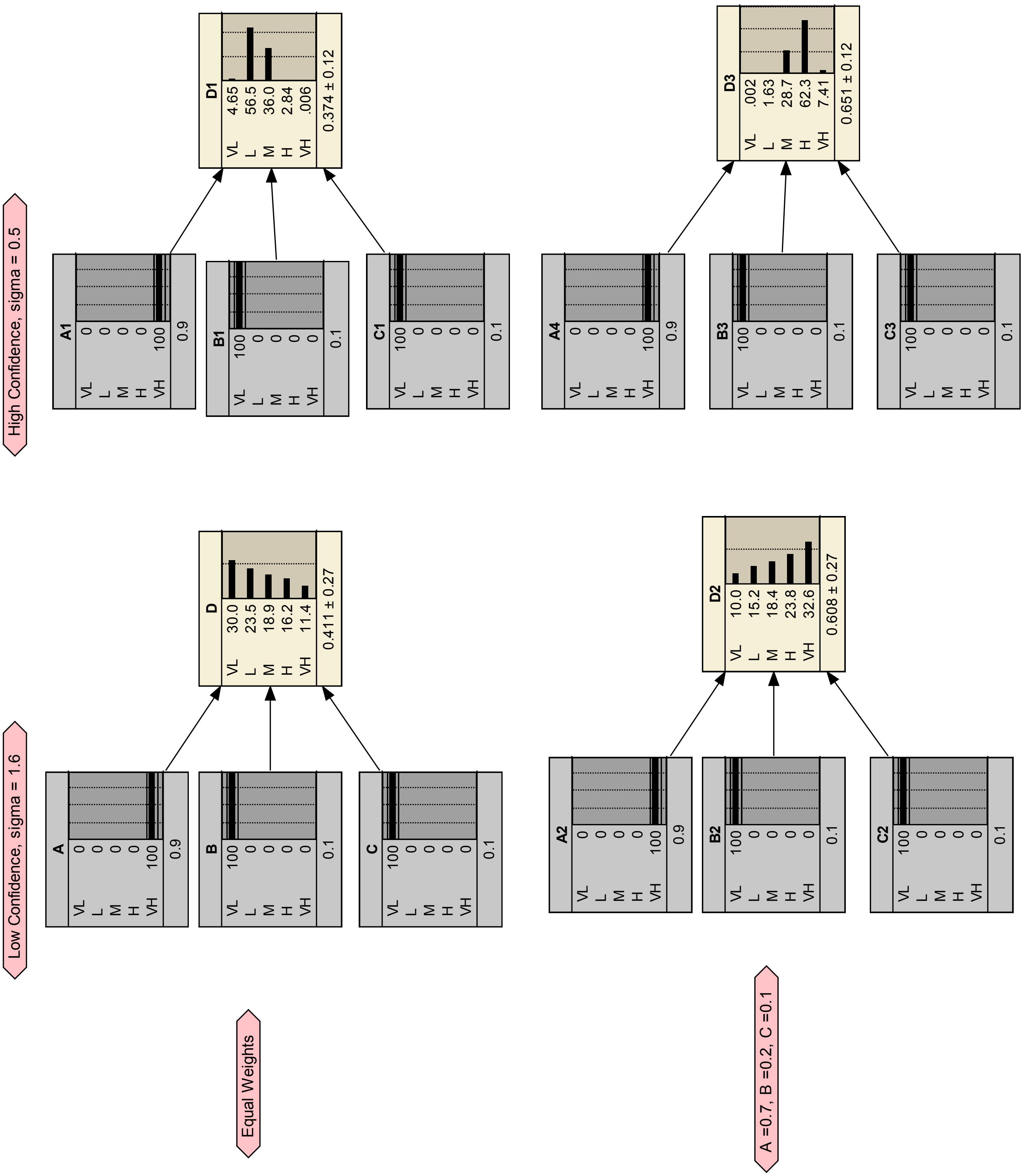


Fig. B4. Posterior BBN when evidence is entered with A = VH, B = VL, and C = VL, for the four cases considered.

B.2. Constraining the CPT so that one or both extreme states do not occur

The current model that uses expert weights for upstream nodes and a level of confidence expressed in these assignments yields predictions for the downstream node that always span the full range of possibilities, that is, from 0 to 1 for X_j, so that nonzero probabilities are assigned to all five states, from VL to VH. What if the expert believes that no matter what, node D can never be in state VL, or on the opposite end, never be in states H or VH? The expert may thus wish to constrain their assessment for node D to a smaller range. This can be accomplished by limiting the logistic normal variable (X) to a range (a, b), with $a > 0$ and $b < 1$, and rescaling its probability distribution so that $F(X = a) = 0$ and $F(X = b) = 1$. Nonzero probabilities (that sum to 1.0) can then be computed for the states with intervals that overlap the range (a, b).

B.3. References

Druzdzel, M.J., Van Der Gaag, L.C., 1995. Elicitation of probabilities for belief networks: combining qualitative and quantitative information, Proceedings of the Eleventh conference on Uncertainty in artificial intelligence. Morgan Kaufmann Publishers Inc., Montreal, Quebec, Canada, pp. 141–148.
Fenton, N.E., Neil, M., Caballero, J.G., 2007. Using Ranked Nodes to Model Qualitative Judgments in Bayesian Networks. IEEE Transactions on Knowledge and Data Engineering 19, 1420–1432.
Laitila, P., Virtanen, K., 2016. Improving Construction of Conditional Probability Tables for Ranked Nodes in Bayesian Networks. IEEE Transactions on Knowledge and Data Engineering 28, 1691–1705.
Mkrtchyan, L., Podofillini, L., Dang, V.N., 2016. Methods for building Conditional Probability Tables of Bayesian Belief Networks from limited judgment: An evaluation for Human Reliability Application. Reliability Engineering & System Safety 151, 93–112.
Renooij, S., 2001. Probability elicitation for belief networks: issues to consider. Knowl. Eng. Rev. 16, 255–269.

Appendix C. Two examples of expert-informed conditional probability tables

To illustrate the structure and content of the fitted CPTs, examples are presented here for Node 6 Transport Cost and Node 33 Perceived Benefits. Since both of these child nodes have three parents and each parent has five states, the number of rows in each CPT = 5^3 = 125.

C.1. Table for node 6. Transport cost

	Parent nodes						
1. Existing pipeline network	2. Transport distance	3. Technology maturity	CPT for node 6. transport cost				
			VL	L	M	H	VH
VL	VL	VL	0.002	0.189	0.581	0.225	0.003
VL	VL	L	0.003	0.22	0.582	0.193	0.002
VL	VL	M	0.004	0.254	0.576	0.164	0.002
VL	VL	H	0.006	0.289	0.566	0.138	0.001
VL	VL	VH	0.008	0.327	0.549	0.115	0.001
VL	L	VL	0	0.047	0.433	0.492	0.028
VL	L	L	0	0.06	0.466	0.453	0.021
VL	L	M	0	0.075	0.497	0.412	0.016
VL	L	H	0.001	0.091	0.524	0.372	0.012
VL	L	VH	0.001	0.112	0.546	0.332	0.009
VL	M	VL	0	0.005	0.173	0.673	0.149
VL	M	L	0	0.008	0.207	0.664	0.121
VL	M	M	0	0.011	0.244	0.648	0.097
VL	M	H	0	0.016	0.281	0.626	0.077
VL	M	VH	0	0.021	0.32	0.599	0.06
VL	H	VL	0	0	0.023	0.467	0.51
VL	H	L	0	0	0.035	0.523	0.442
VL	H	M	0	0.001	0.048	0.573	0.378
VL	H	H	0	0.001	0.067	0.612	0.32
VL	H	VH	0	0.002	0.087	0.643	0.268
VL	VH	VL	0	0	0	0.052	0.948
VL	VH	L	0	0	0.001	0.091	0.908
VL	VH	M	0	0	0.001	0.142	0.857
VL	VH	H	0	0	0.003	0.202	0.795
VL	VH	VH	0	0	0.005	0.268	0.727
1. Existing pipeline network	**2. Transport distance**	**3. Technology maturity**	**CPT for node 6. transport cost**				
L	VL	VL	0.017	0.417	0.493	0.073	0
L	VL	L	0.022	0.458	0.462	0.058	0
L	VL	M	0.029	0.498	0.427	0.046	0
L	VL	H	0.038	0.535	0.392	0.035	0
L	VL	VH	0.049	0.571	0.353	0.027	0
			VL	**L**	**M**	**H**	VH
L	L	VL	0.002	0.168	0.578	0.248	0.004
L	L	L	0.003	0.197	0.582	0.215	0.003
L	L	M	0.004	0.228	0.582	0.184	0.002
L	L	H	0.005	0.263	0.574	0.156	0.002
L	L	VH	0.007	0.299	0.562	0.131	0.001
L	M	VL	0	0.04	0.407	0.519	0.034
L	M	L	0	0.051	0.442	0.481	0.026
L	M	M	0	0.064	0.476	0.44	0.02
L	M	H	0	0.08	0.505	0.4	0.015
L	M	VH	0.001	0.097	0.531	0.36	0.011
L	H	VL	0	0.004	0.15	0.673	0.173
L	H	L	0	0.006	0.182	0.671	0.141
L	H	M	0	0.009	0.217	0.661	0.113
L	H	H	0	0.012	0.254	0.644	0.09
L	H	VH	0	0.017	0.292	0.619	0.072
L	VH	VL	0	0	0.017	0.422	0.561

L	VH	L	0	0	0.026	0.484	0.49
L	VH	M	0	0	0.039	0.538	0.423
L	VH	H	0	0.001	0.053	0.585	0.361
L	VH	VH	0	0.001	0.072	0.622	0.305
M	VL	VL	0.085	0.637	0.264	0.014	0
M	VL	L	0.106	0.657	0.227	0.01	0
M	VL	M	0.132	0.669	0.192	0.007	0
M	VL	H	0.163	0.673	0.159	0.005	0
M	VL	VH	0.199	0.669	0.129	0.003	0
M	L	VL	0.014	0.388	0.513	0.085	0
M	L	L	0.018	0.429	0.485	0.068	0
M	L	M	0.024	0.469	0.453	0.054	0
M	L	H	0.031	0.509	0.418	0.042	0
M	L	VH	0.041	0.546	0.38	0.033	0
M	M	VL	0.001	0.149	0.571	0.274	0.005
M	M	L	0.002	0.176	0.58	0.238	0.004
M	M	M	0.003	0.206	0.582	0.206	0.003
M	M	H	0.004	0.238	0.58	0.176	0.002
M	M	VH	0.005	0.274	0.571	0.149	0.001
M	H	VL	0	0.033	0.38	0.546	0.041
M	H	L	0	0.042	0.418	0.509	0.031
M	H	M	0	0.054	0.453	0.469	0.024
M	H	H	0	0.068	0.485	0.429	0.018
M	H	VH	0	0.085	0.513	0.388	0.014
M	VH	VL	0	0.003	0.129	0.669	0.199
M	VH	L	0	0.005	0.159	0.673	0.163
M	VH	M	0	0.007	0.192	0.669	0.132
M	VH	H	0	0.01	0.227	0.657	0.106
M	VH	VH	0	0.014	0.264	0.637	0.085
H	VL	VL	0.305	0.622	0.072	0.001	0
H	VL	L	0.361	0.585	0.053	0.001	0
H	VL	M	0.423	0.538	0.039	0	0
H	VL	H	0.49	0.484	0.026	0	0
H	VL	VH	0.561	0.422	0.017	0	0
H	L	VL	0.072	0.619	0.292	0.017	0
H	L	L	0.09	0.644	0.254	0.012	0
H	L	M	0.113	0.661	0.217	0.009	0
H	L	H	0.141	0.671	0.182	0.006	0
H	L	VH	0.173	0.673	0.15	0.004	0
H	M	VL	0.011	0.36	0.531	0.097	0.001
H	M	L	0.015	0.4	0.505	0.08	0
H	M	M	0.02	0.44	0.476	0.064	0
H	M	H	0.026	0.481	0.442	0.051	0
H	M	VH	0.034	0.519	0.407	0.04	0
H	H	VL	0.001	0.131	0.562	0.299	0.007
H	H	L	0.002	0.156	0.574	0.263	0.005
H	H	M	0.002	0.184	0.582	0.228	0.004
H	H	H	0.003	0.215	0.582	0.197	0.003
H	H	VH	0.004	0.248	0.578	0.168	0.002
H	VH	VL	0	0.027	0.353	0.571	0.049
H	VH	L	0	0.035	0.392	0.535	0.038
H	VH	M	0	0.046	0.427	0.498	0.029
H	VH	H	0	0.058	0.462	0.458	0.022
H	VH	VH	0	0.073	0.493	0.417	0.017
VH	VL	VL	0.727	0.268	0.005	0	0
VH	VL	L	0.795	0.202	0.003	0	0
VH	VL	M	0.857	0.142	0.001	0	0
VH	VL	H	0.908	0.091	0.001	0	0
VH	VL	VH	0.948	0.052	0	0	0
VH	L	VL	0.268	0.643	0.087	0.002	0
VH	L	L	0.32	0.612	0.067	0.001	0
VH	L	M	0.378	0.573	0.048	0.001	0
VH	L	H	0.442	0.523	0.035	0	0
VH	L	VH	0.51	0.467	0.023	0	0
VH	M	VL	0.06	0.599	0.32	0.021	0
VH	M	L	0.077	0.626	0.281	0.016	0
VH	M	M	0.097	0.648	0.244	0.011	0
VH	M	H	0.121	0.664	0.207	0.008	0
VH	M	VH	0.149	0.673	0.173	0.005	0
VH	H	VL	0.009	0.332	0.546	0.112	0.001
VH	H	L	0.012	0.372	0.524	0.091	0.001
VH	H	M	0.016	0.412	0.497	0.075	0
VH	H	H	0.021	0.453	0.466	0.06	0
VH	H	VH	0.028	0.492	0.433	0.047	0
VH	VH	VL	0.001	0.115	0.549	0.327	0.008
VH	VH	L	0.001	0.138	0.566	0.289	0.006
VH	VH	M	0.002	0.164	0.576	0.254	0.004
VH	VH	H	0.002	0.193	0.582	0.22	0.003
VH	VH	VH	0.003	0.225	0.581	0.189	0.002

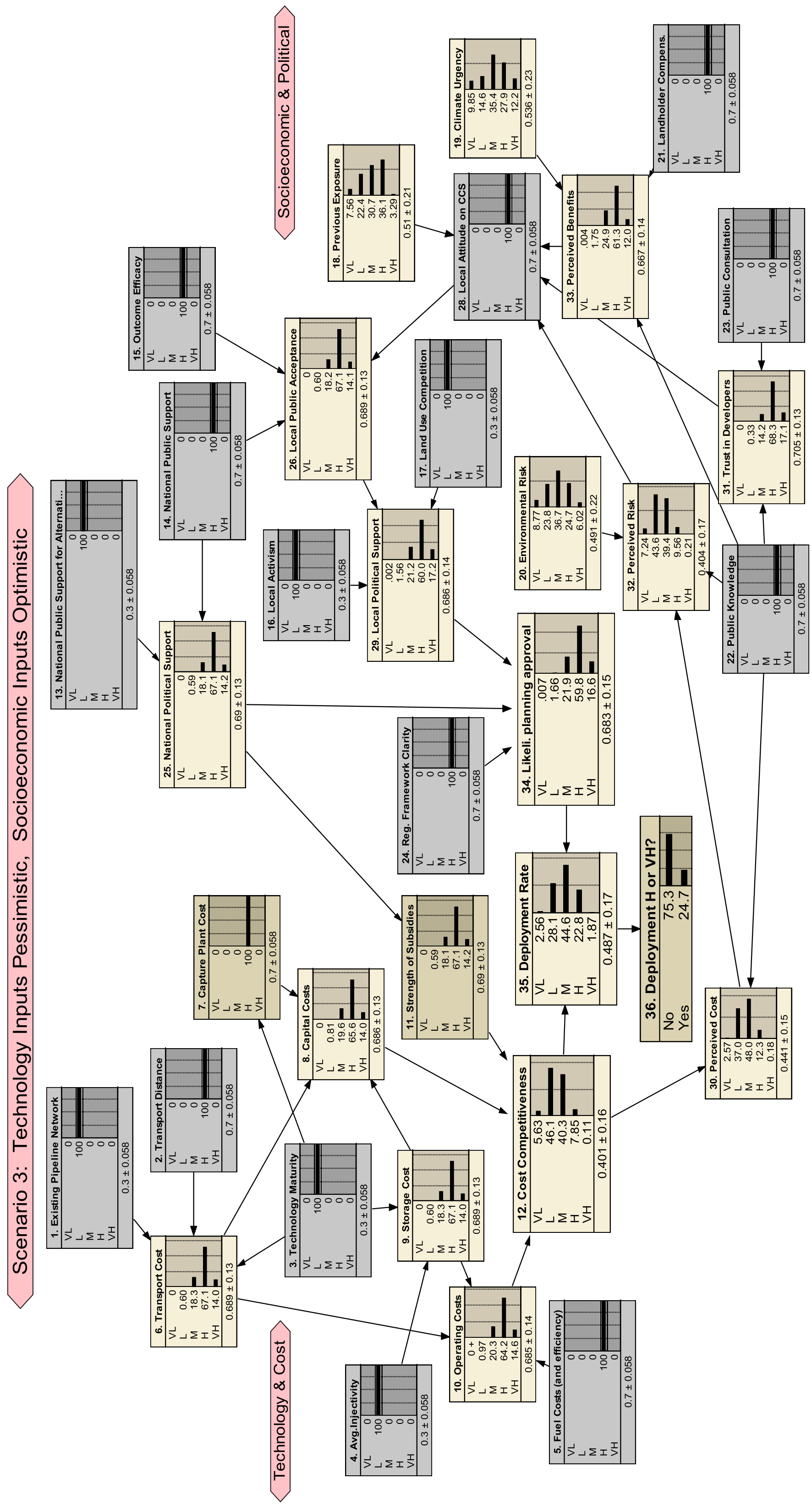
C.2. Table for node 33. Perceived benefits

21. Landholder Compensation	Parent nodes 19. Climate Urgency	22. Public Knowledge	CPT for Node 33. Perceived benefits VL	L	M	H	VH
VL	VL	VL	0.948	0.052	0	0	0
VL	VL	L	0.776	0.221	0.003	0	0
VL	VL	M	0.54	0.44	0.02	0	0
VL	VL	H	0.328	0.607	0.064	0.001	0
VL	VL	VH	0.178	0.672	0.146	0.004	0
VL	L	VL	0.757	0.239	0.004	0	0
VL	L	L	0.52	0.458	0.022	0	0
VL	L	M	0.312	0.618	0.069	0.001	0
VL	L	H	0.168	0.673	0.155	0.004	0
VL	L	VH	0.082	0.633	0.271	0.014	0
VL	M	VL	0.5	0.475	0.025	0	0
VL	M	L	0.297	0.627	0.075	0.001	0
VL	M	M	0.158	0.674	0.163	0.005	0
VL	M	H	0.077	0.626	0.281	0.016	0
VL	M	VH	0.034	0.519	0.407	0.04	0
VL	H	VL	0.283	0.634	0.082	0.001	0
VL	H	L	0.149	0.673	0.173	0.005	0
VL	H	M	0.072	0.619	0.292	0.017	0
VL	H	H	0.031	0.509	0.418	0.042	0
VL	H	VH	0.012	0.378	0.52	0.09	0
VL	VH	VL	0.141	0.671	0.182	0.006	0
VL	VH	L	0.067	0.611	0.303	0.019	0
VL	VH	M	0.029	0.498	0.427	0.046	0
VL	VH	H	0.011	0.366	0.528	0.094	0.001
VL	VH	VH	0.004	0.243	0.579	0.172	0.002
L	VL	VL	0.48	0.492	0.028	0	0
L	VL	L	0.283	0.634	0.082	0.001	0
L	VL	M	0.149	0.673	0.173	0.005	0
L	VL	H	0.072	0.619	0.292	0.017	0
L	VL	VH	0.031	0.509	0.418	0.042	0
L	L	VL	0.268	0.643	0.087	0.002	0
21. Landholder Compensation	**Parent Nodes 19. Climate Urgency**	**22. Public Knowledge**	**CPT for Node 33. Perceived Benefits VL**	**L**	**M**	**H**	**VH**
L	L	L	0.141	0.671	0.182	0.006	0
L	L	M	0.067	0.611	0.303	0.019	0
L	L	H	0.029	0.498	0.427	0.046	0
L	L	VH	0.011	0.366	0.528	0.094	0.001
L	M	VL	0.132	0.669	0.192	0.007	0
L	M	L	0.062	0.603	0.315	0.02	0
L	M	M	0.027	0.486	0.438	0.049	0
L	M	H	0.011	0.354	0.534	0.1	0.001
L	M	VH	0.004	0.233	0.581	0.18	0.002
L	H	VL	0.058	0.594	0.326	0.022	0
L	H	L	0.025	0.475	0.448	0.052	0
L	H	M	0.01	0.343	0.54	0.106	0.001
L	H	H	0.003	0.225	0.581	0.189	0.002
L	H	VH	0.001	0.131	0.562	0.299	0.007
L	VH	VL	0.023	0.464	0.457	0.056	0
L	VH	L	0.009	0.332	0.546	0.112	0.001
L	VH	M	0.003	0.215	0.582	0.197	0.003
L	VH	H	0.001	0.125	0.556	0.311	0.007
L	VH	VH	0	0.064	0.476	0.44	0.02
M	VL	VL	0.124	0.666	0.202	0.008	0
M	VL	L	0.058	0.594	0.326	0.022	0
M	VL	M	0.025	0.475	0.448	0.052	0
M	VL	H	0.01	0.343	0.54	0.106	0.001
M	VL	VH	0.003	0.225	0.581	0.189	0.002
M	L	VL	0.054	0.586	0.336	0.024	0
M	L	L	0.023	0.464	0.457	0.056	0
M	L	M	0.009	0.332	0.546	0.112	0.001
M	L	H	0.003	0.215	0.582	0.197	0.003
M	L	VH	0.001	0.125	0.556	0.311	0.007
M	M	VL	0.021	0.453	0.466	0.06	0
M	M	L	0.008	0.321	0.552	0.118	0.001
M	M	M	0.003	0.206	0.582	0.206	0.003
M	M	H	0.001	0.118	0.552	0.321	0.008
M	M	VH	0	0.06	0.466	0.453	0.021
M	H	VL	0.007	0.311	0.556	0.125	0.001

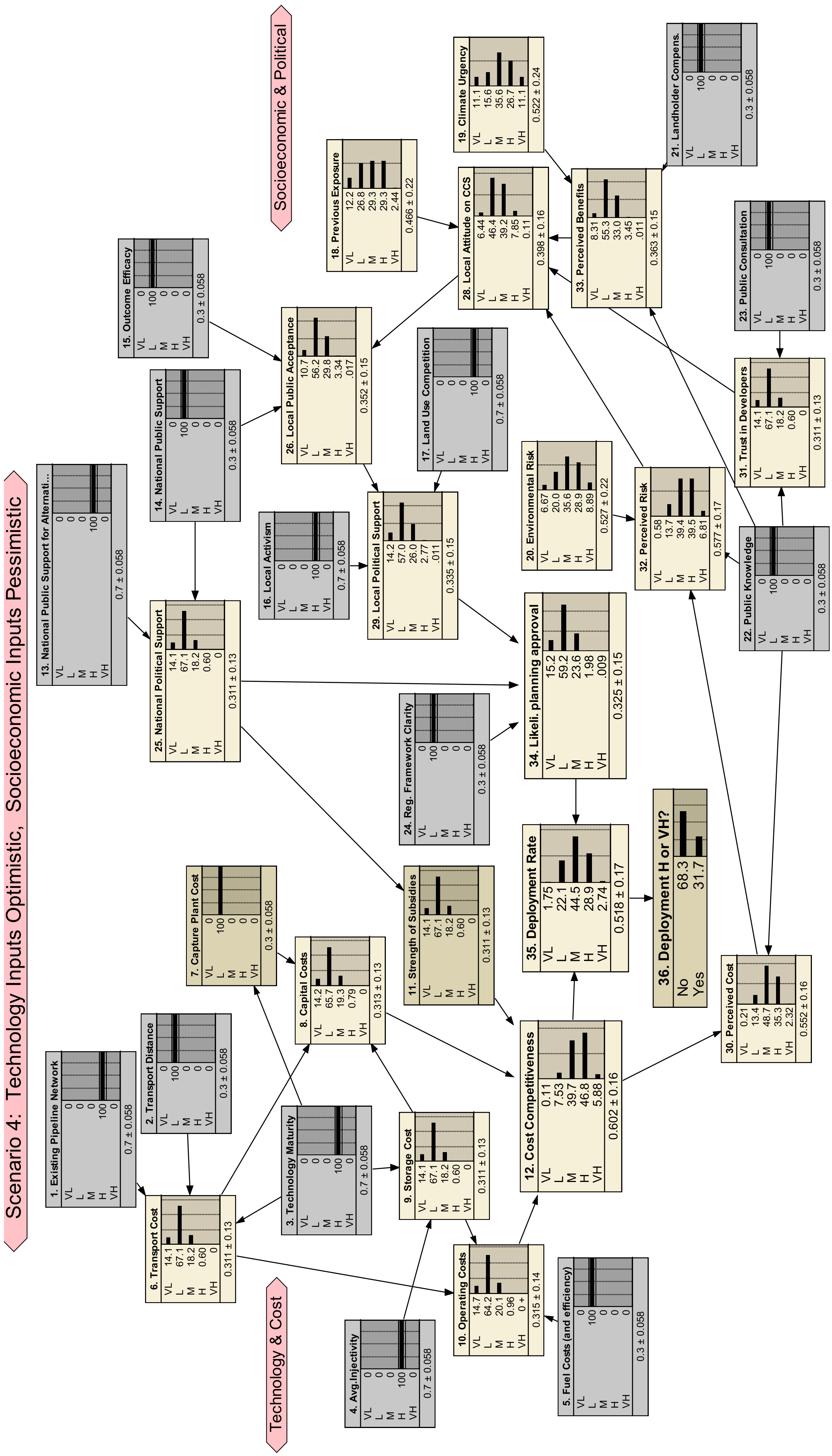
M	H	L	0.003	0.197	0.582	0.215	0.003
M	H	M	0.001	0.112	0.546	0.332	0.009
M	H	H	0	0.056	0.457	0.464	0.023
M	H	VH	0	0.024	0.336	0.586	0.054
M	VH	VL	0.002	0.189	0.581	0.225	0.003
M	VH	L	0.001	0.106	0.54	0.343	0.01
M	VH	M	0	0.052	0.448	0.475	0.025
M	VH	H	0	0.022	0.326	0.594	0.058
M	VH	VH	0	0.008	0.202	0.666	0.124
H	VL	VL	0.02	0.44	0.476	0.064	0
H	VL	L	0.007	0.311	0.556	0.125	0.001
H	VL	M	0.003	0.197	0.582	0.215	0.003
H	VL	H	0.001	0.112	0.546	0.332	0.009
H	VL	VH	0	0.056	0.457	0.464	0.023
H	L	VL	0.007	0.299	0.562	0.131	0.001
H	L	L	0.002	0.189	0.581	0.225	0.003
H	L	M	0.001	0.106	0.54	0.343	0.01
H	L	H	0	0.052	0.448	0.475	0.025
H	L	VH	0	0.022	0.326	0.594	0.058
H	M	VL	0.002	0.18	0.581	0.233	0.004
H	M	L	0.001	0.1	0.534	0.354	0.011
H	M	M	0	0.049	0.438	0.486	0.027
H	M	H	0	0.02	0.315	0.603	0.062
H	M	VH	0	0.007	0.192	0.669	0.132
H	H	VL	0.001	0.094	0.528	0.366	0.011
H	H	L	0	0.046	0.427	0.498	0.029
H	H	M	0	0.019	0.303	0.611	0.067
H	H	H	0	0.006	0.182	0.671	0.141
H	H	VH	0	0.002	0.087	0.643	0.268
H	VH	VL	0	0.042	0.418	0.509	0.031
H	VH	L	0	0.017	0.292	0.619	0.072
H	VH	M	0	0.005	0.173	0.673	0.149
H	VH	H	0	0.001	0.082	0.634	0.283
H	VH	VH	0	0	0.028	0.492	0.48
VH	VL	VL	0.002	0.172	0.579	0.243	0.004
VH	VL	L	0.001	0.094	0.528	0.366	0.011
VH	VL	M	0	0.046	0.427	0.498	0.029
VH	VL	H	0	0.019	0.303	0.611	0.067
VH	VL	VH	0	0.006	0.182	0.671	0.141
VH	L	VL	0	0.09	0.52	0.378	0.012
VH	L	L	0	0.042	0.418	0.509	0.031
VH	L	M	0	0.017	0.292	0.619	0.072
VH	L	H	0	0.005	0.173	0.673	0.149
VH	L	VH	0	0.001	0.082	0.634	0.283
VH	M	VL	0	0.04	0.407	0.519	0.034
VH	M	L	0	0.016	0.281	0.626	0.077
VH	M	M	0	0.005	0.163	0.674	0.158
VH	M	H	0	0.001	0.075	0.627	0.297
VH	M	VH	0	0	0.025	0.475	0.5
VH	H	VL	0	0.014	0.271	0.633	0.082
VH	H	L	0	0.004	0.155	0.673	0.168
VH	H	M	0	0.001	0.069	0.618	0.312
VH	H	H	0	0	0.022	0.458	0.52
VH	H	VH	0	0	0.004	0.239	0.757
VH	VH	VL	0	0.004	0.146	0.672	0.178
VH	VH	L	0	0.001	0.064	0.607	0.328
VH	VH	M	0	0	0.02	0.44	0.54
VH	VH	H	0	0	0.003	0.221	0.776
VH	VH	VH	0	0	0	0.052	0.948

Appendix D. Network Diagrams for Scenario 3 (Technology Constrained) and Scenario 4 (Socially Constrained)

Scenario 3 Technology Constrained:



Scenario 4 Socially Constrained


Scenario 4: Technology Inputs Optimistic, Socioeconomic Inputs Pessimistic
Socioeconomic & Political
Technology & Cost
1. Existing Pipeline Network
2. Transport Distance
3. Technology Maturity
4. Avg.Injectivity
5. Fuel Costs (and efficiency)
6. Transport Cost
7. Capture Plant Cost
8. Capital Costs
9. Storage Cost
10. Operating Costs
11. Strength of Subsidies
12. Cost Competitiveness
13. National Public Support for Alternati...
14. National Public Support
15. Outcome Efficacy
16. Local Activism
17. Land Use Competition
18. Previous Exposure
19. Climate Urgency
20. Environmental Risk
21. Landholder Compens.
22. Public Knowledge
23. Public Consultation
24. Reg. Framework Clarity
25. National Political Support
26. Local Public Acceptance
28. Local Attitude on CCS
29. Local Political Support
30. Perceived Cost
31. Trust in Developers
32. Perceived Risk
33. Perceived Benefits
34. Likeli. planning approval
35. Deployment Rate
36. Deployment H or VH?
No 68.3
Yes 31.7

References

[1] Guivarch C, Rozenberg J, Schweizer V. The diversity of socio-economic pathways and CO_2 emissions scenarios: Insights from the investigation of a scenarios database. Environ Model Softw 2016;80:336–53.
[2] Hall LMH, Buckley AR. A review of energy systems models in the UK: Prevalent usage and categorisation. Appl Energy 2016;169:607–28.
[3] Herbst A, Toro FA, Reitze F, Jochem E. Introduction to energy systems modelling. Swiss J Econ Stat 2012;148:111–35.
[4] Jägemann C, Fürsch M, Hagspiel S, Nagl S. Decarbonizing Europe's power sector by 2050 — Analyzing the economic implications of alternative decarbonization pathways. Energy Econ 2013;40:622–36.
[5] Paltsev S. Energy scenarios: the value and limits of scenario analysis. Wiley Interdiscip Rev Energy Environ 2017;6. e242.
[6] Rosenbloom D. Pathways: An emerging concept for the theory and governance of low-carbon transitions. Glob Environ Chang 2017;43:37–50.
[7] Sgouridis S, Csala D, Bardi U. The sower's way: quantifying the narrowing net-energy pathways to a global energy transition. Environ Res Lett 2016;11:94009.
[8] Bauer N, et al. Shared socio-economic pathways of the energy sector – quantifying the narratives. Glob Environ Chang 2017;42:316–30.
[9] O'Neill BC, et al. A new scenario framework for climate change research: the concept of shared socioeconomic pathways. Clim Change 2014;122:387–400.
[10] Moss RH, et al. The next generation of scenarios for climate change research and assessment. Nature 2010;463:747–56.
[11] Price J, Keppo I. Modelling to generate alternatives: A technique to explore uncertainty in energy-environment-economy models. Appl Energy 2017;195:356–69.
[12] Riahi K, et al. The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: an overview. Glob Environ Chang 2017;42:153–68.
[13] Enserink B, Kwakkel JH, Veenman S. Coping with uncertainty in climate policy making: (Mis)understanding scenario studies. Futures 2013;53:1–12.
[14] Schweizer VJ, O'Neill BC. Systematic construction of global socioeconomic pathways using internally consistent element combinations. Clim Change 2014;122:431–45.
[15] Trutnevyte E, Guivarch C, Lempert R, Strachan N. Reinvigorating the scenario technique to expand uncertainty consideration. Clim Change 2016;135:373–9.
[16] Schweizer VJ, Kurniawan JH. Systematically linking qualitative elements of scenarios across levels, scales, and sectors. Environ Model Softw 2016;79:322–33.
[17] van Vuuren DP, et al. A new scenario framework for climate change research: scenario matrix architecture. Clim Change 2014;122:373–86.
[18] Fortes P, Alvarenga A, Seixas J, Rodrigues S. Long-term energy scenarios: Bridging the gap between socio-economic storylines and energy modeling. Technol Forecast Soc Change 2015;91:161–78.
[19] Braunreiter L, Blumer YB. Of sailors and divers: How researchers use energy scenarios. Energy Res Soc Sci 2018;40:118–26.
[20] Rogelj J, et al. Scenarios towards limiting global mean temperature increase below 1.5 °C. Nat Clim Chang 2018;8:325–32.
[21] Wiebe K, et al. Scenario development and foresight analysis: Exploring options to inform choices. Annu Rev Environ Resour 2018;43:545–70.
[22] Ringrose PS. Principles of sustainability and physics as a basis for the low-carbon energy transition. Pet Geosci 2017;23:287–97.
[23] IPCC. Climate change 2014: mitigation of climate change. Contribution of working group III to the fifth assessment report of the intergovernmental panel on climate change. Cambridge University Press; 2014.
[24] de Coninck H, et al. The acceptability of CO_2 capture and storage (CCS) in Europe: An assessment of the key determining factors: Part 1. Scientific, technical and economic dimensions. Int J Greenh Gas Control 2009;3:333–43.
[25] Markusson N, et al. A socio-technical framework for assessing the viability of carbon capture and storage technology. Technol Forecast Soc Change 2012;79:903–18.
[26] Shackley S, et al. The acceptability of CO_2 capture and storage (CCS) in Europe: An assessment of the key determining factors: Part 2. The social acceptability of CCS and the wider impacts and repercussions of its implementation. Int J Greenh Gas Control 2009;3:344–56.
[27] Terwel BW, Harinck F, Ellemers N, Daamen DDL. Going beyond the properties of CO_2 capture and storage (CCS) technology: How trust in stakeholders affects public acceptance of CCS. Int J Greenh Gas Control 2011;5:181–8.
[28] Borsuk ME, Stow CA, Reckhow KH. A Bayesian network of eutrophication models for synthesis, prediction, and uncertainty analysis. Ecol Modell 2004;173:219–39.
[29] Catenacci M. Integrated assessment of sea-level rise adaptation strategies using a Bayesian decision network approach. Environ Model Softw 2013;44:87–100.
[30] Gerstenberger MC, Christophersen A. A Bayesian network and structured expert elicitation for Otway Stage 2C: Detection of injected CO2 in a saline aquifer. Int J Greenh Gas Control 2016;51:317–29.
[31] Gerstenberger MC, Christophersen A, Buxton R, Nicol A. Bi-directional risk assessment in carbon capture and storage with Bayesian Networks. Int J Greenh Gas Control 2015;35:150–9.
[32] Krause J, Small MJ, Haas A, Jaeger CC. An expert-based bayesian assessment of 2030 German new vehicle CO2 emissions and related costs. Transp Policy 2016;52:197–208.
[33] Richards R, et al. Bayesian belief modeling of climate change impacts for informing regional adaptation options. Environ Model Softw. 2013;44:113–21.
[34] Stiber N, Pantazidou M, Small MJ. Expert system methodology for evaluating reductive dechlorination at TCE sites; 1999.
[35] Yang Y-M, et al. A Bayesian belief network (BBN) for combining evidence from multiple CO2 leak detection technologies. Greenh Gases Sci Technol 2012;2:185–99.
[36] Daim T, Kayakutlu G, Suharto Y, Bayram Y. Clean energy investment scenarios using the Bayesian network. Int J Sustain Energy 2014;33:400–15.
[37] Düspohl M, Döll P. Causal networks and scenarios: participatory strategy development for promoting renewable electricity generation. J Clean Prod 2016;121:218–30.
[38] Gambelli D, Alberti F, Solfanelli F, Vairo D, Zanoli R. Third generation algae biofuels in Italy by 2030: A scenario analysis using Bayesian networks. Energy Policy 2017;103:165–78.
[39] Mallampalli VR, et al. Methods for translating narrative scenarios into quantitative assessments of land use change. Environ Model Softw 2016;82:7–20.
[40] Suharto Y. Study of multi-scenario based technology roadmapping: Bayesian causal maps approach. In: Technology management in the IT-driven services (PICMET), proceedings of PICMET'13: (pp. 2212-2218). IEEE; 2013.
[41] Xin P, Khan F, Ahmed S. Dynamic hazard identification and scenario mapping using Bayesian network. Process Saf Environ Prot 2017;105:143–55.
[42] Borunda M, Jaramillo OA, Reyes A, Ibargüengoytia PH. Bayesian networks in renewable energy systems: A bibliographical survey. Renew Sustain Energy Rev 2016;62:32–45.
[43] Chee YE, et al. Modelling spatial and temporal changes with GIS and Spatial and Dynamic Bayesian Networks. Environ Model Softw 2016;82:108–20.
[44] Wu PP-Y, et al. Managing seagrass resilience under cumulative dredging affecting light: Predicting risk using dynamic Bayesian networks. J Appl Ecol 2018;55:1339–50.
[45] Korb K, Nicholson A, Nicholson AE. Bayesian artificial intelligence, 2nd ed., CRC Press; 2010, 20101639.
[46] Norsys. Netica; 2014.
[47] Neapolitan RE. Learning Bayesian networks. Pearson Prentice Hall; 2004.
[48] Nemet GF, Anadon LD, Verdolini E. Quantifying the effects of expert selection and elicitation design on experts' confidence in their judgments about future energy technologies. Risk Anal 2017;37:315–30.
[49] Verdolini E, Anadón LD, Baker E, Bosetti V, Aleluia Reis L. Future prospects for energy technologies: insights from expert elicitations. Rev Environ Econ Policy 2018;12:133–53.